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OPTIMAL DAY-AHEAD SCHEDULING OF A HYBRID ELECTRIC GRID USING WEATHER FORECASTS

by

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December 2013

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The weather forecasts used as a key factor to establish the optimal plan are subject to uncertainty. In order to mitigate this problem, multiple weather forecast scenarios are used in the optimization. This thesis alters the optimization model to represent various configurations of the HEG and optimizes over a variety of weather forecasts. It then tests the operating plans suggested by the model using particular weather scenarios representing actual observed weather conditions. Finally, this thesis gives an illustration of how to run the optimization model with the rolling horizon method using
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ABSTRACT

The compromise between the stability of a hybrid electric grid (HEG) and the total operating cost can be reached by accurately anticipating the future renewable power productions. This thesis suggests the use of weather forecasts to establish day-ahead operating schedules for a grid that include the operating plan of dispatchable fuel-based generators, the charge or discharge of energy storage units, and the energy to exchange with the commercial grid if the configuration of the HEG allows it.

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LIST OF ACRONYMS AND ABBREVIATIONS

BBTU	billion British thermal units
CAES	compressed air energy storage
DHS	Department of Homeland Security
DLIFLC	Defense Language Institute Foreign Language Center
DoD	Department of Defense
DRPs	demand response programs
EMC	energy management center
ES	energy storage
ESS	energy storage system
FAA	Federal Aviation Administration
FOB	forward operating base
GFS	Global Forecast System
GHG	greenhouse gases
GW	gigawatt
GWEC	Global Wind Energy Council
HEG	hybrid electric grid
HRES	hybrid renewable energy system
IHEG	isolated hybrid electric grid
IHRES	isolated renewable energy system
kW	kilowatt
kWh	kilowatt-hours
MM5	Fifth-Generation Penn State/NCAR Mesoscale Model
MW	megawatt
MWh	megawatt-hours
NDAA	National Defense Authorization Act
NREL	National Renewable Energy Laboratory
PV	photovoltaic
PHS	pumped-hydroelectric energy storage
RES	renewable energy source
WRF	Weather Research and Forecasting model

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EXECUTIVE SUMMARY

Integration of renewable energy sources is hampered by the intermittent nature of these sources, which threatens the stability of the electric grid. For instance, wind power and the photovoltaic (PV) power production are very dependent on the weather conditions. Knowing with acceptable accuracy the future wind speed and the insolation, one can predict the future wind power and PV power production. The energy management center controlling a hybrid electric grid (HEG) can use those predictions to manage more effectively the dispatchable fuel-based generators.

The thesis provides a mathematical model of a HEG that includes fuel-based generators, wind turbines, PV panels, energy storage units, and possible connections to the commercial grid. The model uses weather forecasts to establish an optimal day-ahead schedule of the HEG; this schedule is robust and cost efficient.

In order to solve the problem of uncertainty in weather forecasts, we use multiple scenarios of weather forecasts. We exercise the model by optimizing over single scenarios, over subsets of scenarios simultaneously, over the average of all scenarios and over the average of renewable power from all the scenarios. We also alter the model to represent different configurations of the HEG, such as the presence or absence of energy storage and a possible connection to a commercial grid. We find that the optimal operating cost varies considerably with the forecast scenario over which we are optimizing. We also find preliminary results indicating that the integration of energy storage has a significant effect on the operating cost only for isolated ("island") HEG configurations where the energy stored is used to compensate for small power shortfalls that would otherwise be satisfied by small and expensive backup generators. This thesis also tests the suggested operating plans generated from different optimization methods with particular weather scenarios representing the observed weather.

Finally, we provide an illustration on how to run the model using a rolling horizon technique based on updates of weather forecast to eliminate the effect of initial conditions and the end-of-horizon effect and to generate a more robust plan.

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I. INTRODUCTION

A variety of economic, strategic, and environmental considerations make adoption of renewable energy sources by the Department of Defense (DoD) an extremely attractive prospect. However, the intermittent nature of these sources impacts the stability of the electric grid and limits their application. This issue is even more serious in small electric grids such as those usually installed in forward operating bases (FOBs). This issue can be partially overcome by properly planning grid operations. Ideally, an operating plan should anticipate any fluctuation in the renewable power output and respond accordingly.

This thesis develops a mathematical model for optimizing generator usage based on meteorological forecasts used to predict wind and solar power output. This model can be used by an energy manager to determine an operating schedule, or by a planner to assess the performance capabilities of a proposed system. The model accounts for weather forecast uncertainty by including multiple weather scenarios. Before describing our model in detail, we give a brief overview of the current DoD energy portfolio and the factors influencing its evolution.

A. OVERVIEW OF THE ENERGY SITUATION IN THE U.S. GOVERNMENT AND DEPARTMENT OF DEFENSE

The federal government is the largest energy consumer in the United States. In 2008, federal expenses on electricity and fuel were $24.5 billion [1]. The DoD accounts for roughly 80% of this government's energy consumption [2]. On an annual basis, the DoD consumes approximately 125 million barrels of petroleum and 30 million megawatt-hours (MWh) of electricity, which is enough energy to meet the annual needs of about 13 million automobiles and 3 million homes, respectively (assuming 30 miles/gallon and 12,500 miles/year for a typical automobile and 10,000 kilowatt hours (kWh) per year for a typical household) [3]. A number of DoD analyses over the last decade have cited the military's traditional energy approach and its fossil fuel dependence in particular as strategic risks, and they have identified renewable energy and energy efficiency investments as key risk alleviation measures [3].

Since the 1970s, successive administrations have focused on the dangers of the energy system and its reliance on foreign fossil fuel. Many policies were designed to mitigate this dependence, to improve energy security, and to reduce energy costs. Given the magnitude of the government's energy consumption, these policies have been steadily aimed at the federal government's energy use. In January 2007, President Bush signed Executive Order 13423 requiring federal agencies to reduce energy intensity by 3% annually through 2015 or by 30% by 2015, compared to the 2003 level [4]. Later, in 2009, in the Executive Order 13514, President Obama specified that 20% of the DoD's energy consumption should come from renewable sources by 2020. The same executive order aimed at improving the federal government's environmental sustainability by setting a 28% reduction target for government greenhouse gas emissions by 2020 with an estimated energy savings target of $8 billion to $11 billion [5].

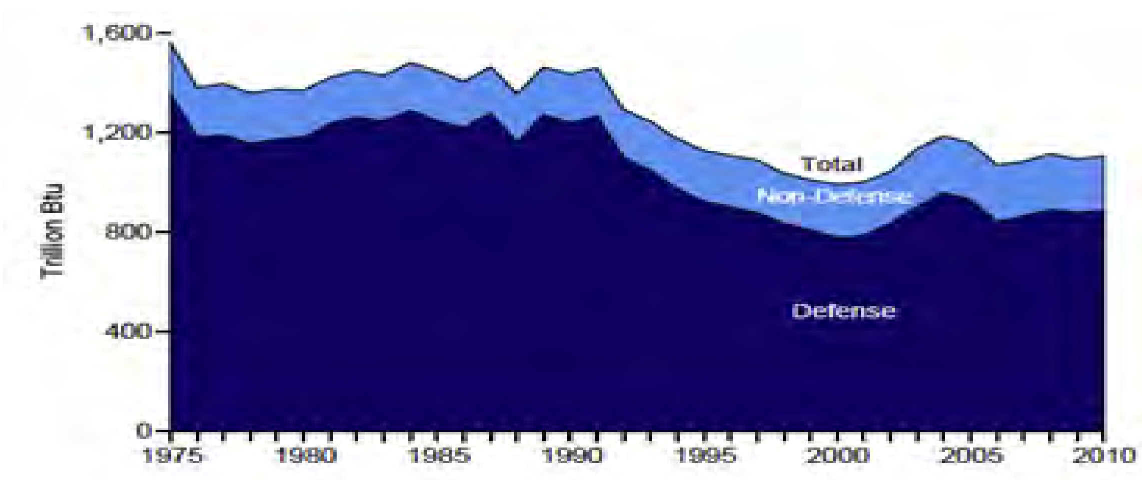

Figure 1. U.S. Government and DoD energy usage in trillions of British thermal units (Btu) in fiscal years 1975–2010 (from [6])

As the government's largest energy consumer, the DoD will play an important and decisive role in meeting the goals set by the Bush and Obama administrations. The DoD energy system is heavily based on fossil fuel, which increases its vulnerability. Additionally, the supply of energy to warfighters at the front lines or in remote settings is extremely costly in terms of monetary value and human losses. The total cost of fuel can be as high as $400 per gallon by the time it is delivered to a remote (FOB) in Afghanistan [7], and one out of every 50 military fuel resupply convoys in that country sustains a fatality or serious injury [8]. Besides the high purchase cost of fuel, supply lines are vulnerable because fuel is usually shipped via unsecured areas and narrow straits such as the Strait of Hormuz.

The price volatility of energy adds an extra burden. For instance, Ray Mabus, the Secretary of the Navy, has stated that every $1 increase in the price of a barrel of oil causes a $31 million increase in the U.S. Navy's energy costs [9]. In the two-year period 2009-2011, oil prices ranged from $71/barrel to $117/barrel, resulting in a $1.1 billion range in budgeting uncertainty [3]. The problems resulting from high volatility in energy prices are not limited to budgeting uncertainties or additional financial burdens; they also pose strategic risks to the troops on the front line.

In order to address the previously-identified issues relevant to the energy usage and supply in the DoD, the 2007 National Defense Authorization Act (NDAA) set a goal that 25% of all DoD energy consumption should be satisfied by renewable energy [10]. To achieve this goal, the DoD encouraged each service branch to establish its own strategic energy plan. In the words of Ray Mabus, a new energy plan for the DoD "is not a fad" and the reasons for adopting it are "strategic, […] tactical and […] essential to our national security" [9].

As the largest consumer of liquid fuels, the Air Force fixed a goal of acquiring 50% of its domestic aviation fuel from domestic synthetic (i.e., non-petroleum) sources by 2016 [11]. The Navy, with a daily consumption of 80,000 barrels of oil for the fleet and 20,000 MWh of electricity for installations on shore, has planned to sail the "Great Green Fleet," a carrier strike group composed of nuclear ships, hybrid electric ships running on biofuels, and aircraft flying on biofuels by 2016, and to make half of its bases net-zero energy facilities by 2020 [12].

The DoD's energy use is divided into two types: the first type is *operational energy*, which is used by military forces for the accomplishment of their missions.

Operational energy comprised 74% of the DoD's total energy consumption in FY 2010, as shown on the left pie chart in Figure 2. The remaining 26% consists of *facilities energy*, which is used at permanent military installations in the United States and abroad. From the energy consumption report for 2010, facilities energy cost approximately $4.0 billion in 2010, and it accounted for 40% of the total greenhouse gases (GHG) created by DoD energy use.

In addition to its environmental detriment, facilities energy has a crucial issue related to its strong dependence on a vulnerable and fragile commercial electricity grid. For instance, in August 2003, a widespread power outage occurred throughout parts of the Northeastern and Midwestern United States and the Canadian province of Ontario. An estimated 45 million people in eight U.S. states were affected. Military installations heavily dependent on commercial grids can also be affected by similar disruption of electricity supply. As stated by Dorothy Robyn, Deputy Under Secretary of Defense for Installations and Environment, "DoD's reliance on a fragile commercial grid places the continuity of critical missions at risk" [13].

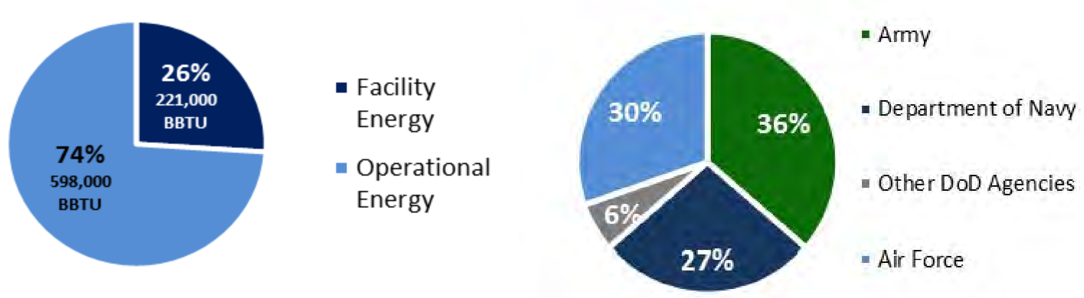

Figure 2. DoD Energy Use in FY 2010 (from [14])

B. RENEWABLE ENERGY USAGE WITHIN THE DEPARTMENT OF DEFENSE

1. The Current State of DoD Renewable Energy Production

Both the environmental impact of a facility's energy consumption and its vulnerability justify special consideration in the new energy plan; thus, the Energy Consumption Report for FY 2010 only addresses facilities energy [14]. This report notes that the DoD fell short of its goals for energy intensity, renewable energy use, and petroleum consumed by non-tactical vehicles. The report also sets priorities to keep up with the milestones of 2020 energy goals, including reducing facilities energy demand, enhancing energy security, facilitating innovative energy research and development, and increasing the use of renewable energy sources (RES).

The Energy Consumption Report for FY 2010 also notes that the DoD already utilizes a variety of renewable sources of energy, including geothermal, solar thermal, solar photovoltaic, and wind energy (see Table 1). Renewable energy production is still very limited in comparison to the total facilities energy demand, which was around 211,000 billion British thermal units (BBTU) in 2010, the majority of which (80%) consisted of demand for electricity and natural gas. Geothermal energy production is the dominant renewable source of energy; in 2010 it provided 74% of the DoD's total renewable energy production of 5,806 BBTU.

Table 1. The DoD's renewable energy production in FY 2010 (from [14])

Sum of Total Output (Electric + Non-electric) (BBTU)								
Renewable Energy Type	Air Force	Army	DLA	Marine Corps	Navy	NSA	TMA	DoD Total
Biogas (captured methane)	.	175	.	.	.	.	.	175
Day lighting	7	2	.	1	.	.	.	10
Geothermal	1	.	.	.	4,292	.	.	4,293
Ground source heat pumps	332	5	.	4	18	.	.	350
Hydropower	.	60	.	.	.	.	.	60
Landfill gas	52	.	.	.	.	.	.	52
Solar photovoltaic	20	14	0.01	22	25	0.05	.	81
Solar thermal	6	11	.	1	34	.	.	52
Wind	57	6	.	16	50	.	.	129
Wood and wood residuals	.	11		.	.	.	.	11
Municipal solid waste	.	.	.	.	538		47	586
Total	474	284	0.01	44	4,957	0.05	47	5,806

2. Wind Power in the DoD

In comparison with geothermal energy, the DoD's wind power production is still insignificant, despite the fact that wind power is one of the most abundant and promising renewable energy resources in terms of its production capacity and cost. New technologies have made wind turbines more efficient with a production capacity that can reach many megawatts (see Figure 3).

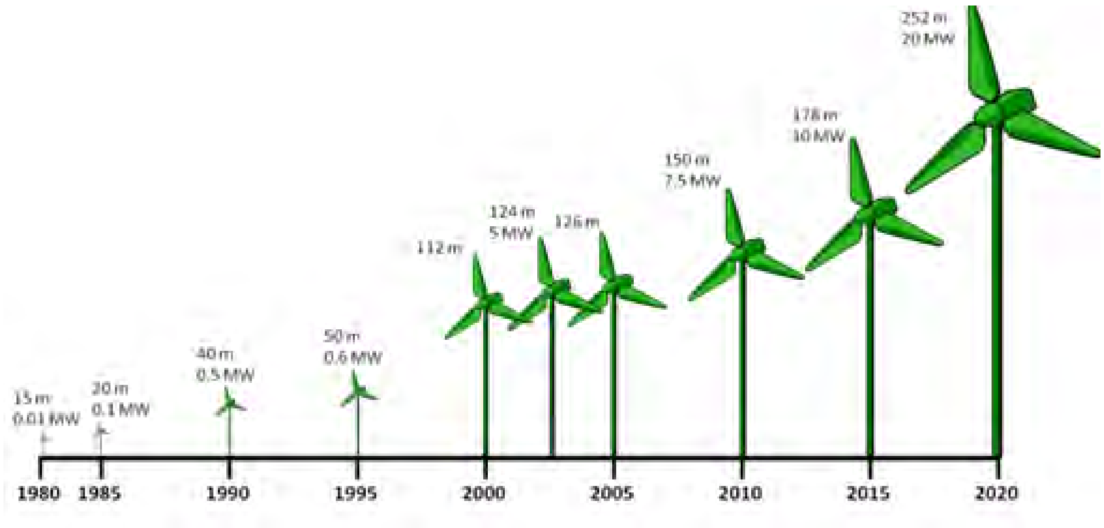

Figure 3. Evolution of wind turbine dimensions and production capacities (from [15])

Global wind power production reached 282.5 gigawatts (GW) at the end of 2012 [16], with a cumulative capacity growth of about 19% (see Figure 4). Due to the financial crisis that occurred in 2009 and 2010, this is considered by the Global Wind Energy Council (GWEC) to be excellent growth.

Nationwide, the U.S. has abundant and strong wind resources. Potential wind energy production capacity is estimated to be 10 times the amount of electricity needed for the entire country [17]. By the end of 2012, the U.S. wind fleet had a production capacity of 60 GW; this is enough electricity for 15.5 million American homes, or the same amount of electricity as 10 nuclear power plants [16]. This 60 GW wind power capacity reduces carbon dioxide (CO_2) emissions annually by about 100 million metric tons. In addition, it conserves over 35 billion gallons of water annually by reducing consumption in thermal power plants [16].

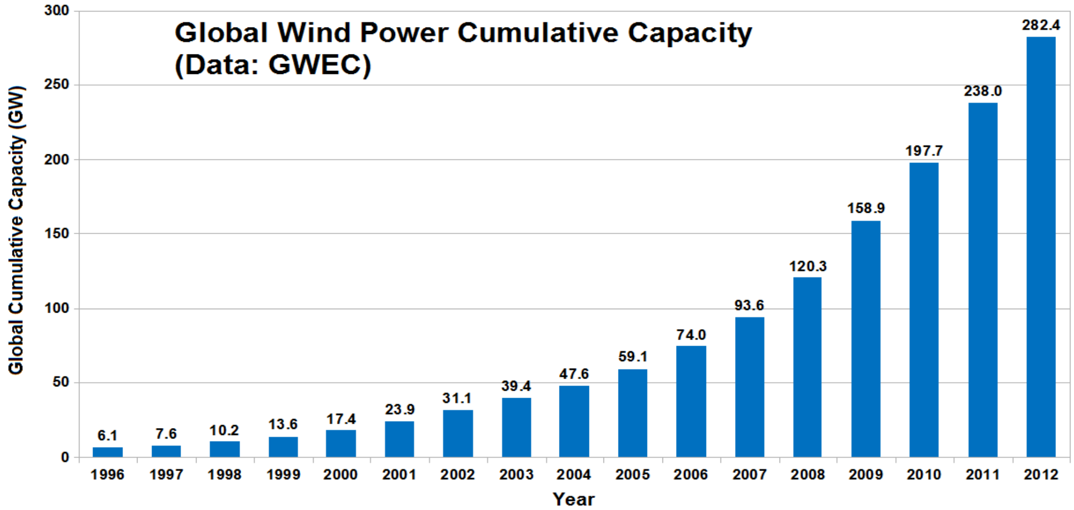

Figure 4. Global cumulative installed wind capacity 1996-2012 (from [18])

Despite its abundance, wind energy is not significantly contributing to the DoD's energy production. In 2010, wind comprised only 2.2% of total DoD renewable energy production; this is despite the fact that many military establishments, especially naval bases, are located in areas gifted with strong and abundant wind.

Initially, the DoD was reluctant to construct wind turbines at military facilities, or even in nearby areas, because of suspicions about the risk of interference between wind turbines and radar systems [19]. As the only agencies in the United States certified to judge that a particular mitigation to radar interference is sufficient, the Federal Aviation Administration (FAA), the Department of Homeland Security (DHS), and the Department of Defense conducted many studies and tests on various mitigation techniques.

Studies conducted at the National Renewable Energy Laboratory (NREL) [20] and the MITRE Corporation [21] presented many techniques for mitigating the impact of wind farms on radar systems. These techniques can be divided into *modifications of the wind farm* and *modifications of the radar*.

Techniques for modifying the wind farm include:

- Modification of turbine blades to reduce their radar signature [21]

- Transmission of turbine telemetry (angular velocity, phase, and pitch angle) to radar processors in order to eliminate turbine radar returns while preserving returns from objects of interest [21].
- Selection of turbine locations to reduce impact [20].

Radar system modifications include modifications of both radar hardware and radar software. These modifications include:

- Adjustment of the look angle and selective use of multiple beams [20].
- Shortening of pulses and increase in pulse repetition frequency; and use of local oscillators coherent over a turbine blade period [21].

Other techniques involve modification of aircraft; one example is the integration of transponders in aircraft flying over wind farms in order to provide a direct way to distinguish them from hostile aircraft, which fly without transponders.

The effectiveness of some of these techniques was tested in a number of operational field tests such as an FAA test in King Mountain, Texas, home to a 280-megawatt (MW) wind farm with 214 turbines [22]. In July 2011, the DoD declared that a complete study of 217 wind farm projects proposed in 35 states and Puerto Rico found that 200 of these projects would have little or no impact on military missions [23]. After successful mitigation of the problems associated with radar interference, more and more wind farms were erected or are under construction within military facilities. Some notable examples include the 3.32-MW wind generation facility at F. E. Warren Air Force Base, Wyoming, the 4.5-MW facility at Otis Air Force Base, Massachusetts, and the new 9-MW wind generation project at Naval Station Newport, Rhode Island.

3. Solar-Generated Electricity (Photovoltaic Power)

A photovoltaic (PV) array is a set of photovoltaic modules, also known as solar panels, that converts solar radiation (sunlight) into usable direct current electricity. Historically, a major disadvantage of solar power is its high cost, which explains the limited investment in this clean renewable source of energy before 2010 and 2011, as shown in Figure 5.

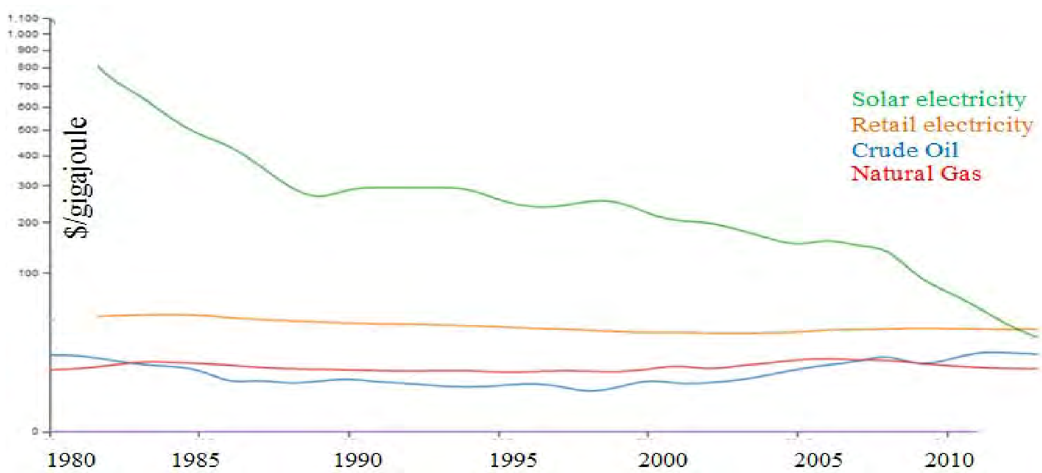

Figure 5. Production costs of various forms of energy (from [24])

The cost of solar panels has continually decreased; for instance, in the second quarter of 2013, the cost per unit energy produced by solar panels was approximately 60% less than in early 2011 [25]. Many factors led to this decrease. Among these factors were technological and manufacturing developments that allow for the production of cheaper and more efficient PV cells. According to the clean technology-focused website *CleanTechnica.com*, economies of scale were responsible for the decrease in installed solar panel costs; as more solar panels are manufactured, costs come down. This also leads to market maturation and the emergence of new competitors driving down the price of solar energy [25]. The impact of this reduction in cost has been striking; in the 12-month period ending in July 1013, the total solar energy produced in the United States was 6,407 gigawatt-hours, double of the amount produced in the same period of time ending in July 2012 [26]. Figure 6 illustrates this dramatic increase.

Solar-generated energy has also been a key focus for the DoD, and many projects and evaluation studies have been conducted. After its completion, the Fort Irwin solar plant in the Mojave Desert will be the largest renewable energy project in the military's history. The project will cover more than 21 square miles (similar to the size of Manhattan), and its initial production capacity will exceed 500 MW, with an additional 1000-MW expansion possible [28]. The DoD also has many smaller-scale solar arrays such as the 14.2-MW photovoltaic solar array at Nellis Air Force Base, and the 6-MW photovoltaic solar array at the Air Force Academy.

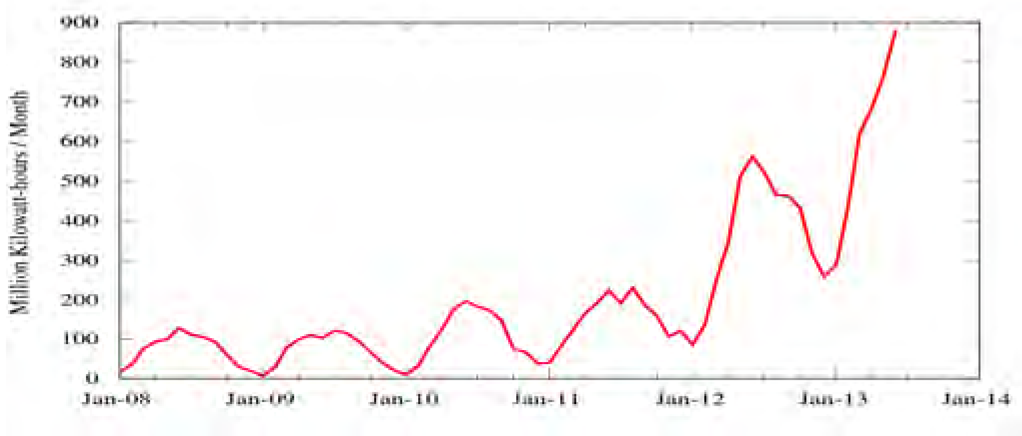

Figure 6. U. S. Monthly Solar-Generated Electricity (from [27])

C. CHALLENGES IN INTEGRATING RENEWABLE ENERGY

1. Issues Related to Wind and Photovoltaic Energy

Even though it is widely recommended and cost efficient, renewable energy constitutes only a small fraction of the electric grid load. The fraction of the total load satisfied by renewable energy, known as the *energy penetration*, is approximately 5–15%. This low energy penetration does not result from a limitation in availability, but from the intermittent nature of renewable production. Both wind power production and PV solar production are unpredictable, and their resulting power output can vary considerably within a short time interval (e.g., an hour) in addition to seasonally (e.g., in summer vs. winter).

Wind power production can be very significant if the wind is blowing at a high speed, but it can quickly shut down if the wind speed decreases. If the fluctuation of wind power production is significant relative to the total load, the grid can be very unstable and in some cases blackouts may even occur. On the other hand, electricity is an instant-time product: after being generated, as it must be used immediately or it will be lost. This fact limits the efficiency of non-controllable renewable energy resources. In addition to being highly variable, renewable sources often suffer from a mismatch between peak production and peak demand. For example, the average wind speed is typically higher at night when the load demand is low [29], and solar output decreases in winter, when more energy is needed for heating buildings. On a day-to-day basis, however, PV solar energy can be integrated into the electric grid more efficiently than wind power, because the daily peak of insolation, which is also the peak of PV power production, coincides with the peak of demand.

2. Remedies to Renewable Energy Intermittence

a. Combining Wind and PV Power

The misalignment between wind energy supply and demand restricts wind energy penetration, especially during peak hours. As a remedy to that problem, some systems combine wind turbines with photovoltaic cells to smooth out the total renewable power output, and make it less volatile. According to a study done by the Reiner Lemoine Institut and Solarpraxis AG, solar power and wind power generation complement each other more effectively than was previously thought [30]. The study focused on the case where solar photovoltaic systems and wind turbines are installed in the same area. This configuration can produce twice the amount of electricity in the same area [30]. The loss in photovoltaic production caused by the shading produced by the wind turbines was estimated to be a mere 1–2% of the nominal production [30].

This combined and compact configuration does not require grid expansion since these resources generate power at different time intervals and during complementary periods. A reduction in the productivity of wind turbines in clear, non-windy weather can be offset by the photovoltaic system, and vice versa in opposite weather conditions. The peak power will not increase considerably, but the penetration level to the total grid can be safely increased because the level of energy provided to the grid is steadier than that for a hybrid system that uses only wind turbines or photovoltaic systems alone [30].

b. Energy Storage

Combining both solar photovoltaic systems and wind turbines can be a reliable and efficient solution to relieve the intermittence and variability of solar and wind energy production. In practice, however, this may not be enough. For example, when the overnight wind power production is very significant relative to the load, not all of the wind power produced can be used immediately. In such cases, it is desirable to store the surplus power produced. The idea of energy storage (ES) is an old concept that has many techniques and methods. The most common energy storage technique is the use of batteries that store convertible chemical energy to run electronic devices. Other examples of evolving techniques adopted to store energy are flywheels, compressed air energy storage (CAES) and pumped-hydro energy storage (PHS), which uses the excess of electricity production to pump water to a dam at a higher level and later use the gravitational potential energy to run hydraulic generators. Table 2 presents a comparison of CAES, PHS, and flywheels.

Table 2. Comparison of some energy storage options (from [31])

	Flywheels	Pumped Hydro	Compressed Air
Power density	Very Good	Very Good	Very Good
Energy density	Fair	Very Good	Very Good
Life time	20 years	30 years	30 years
Recharge Time	Excellent	Variable	Fair
Maintenance cost	Moderate	High	Low
Environment	Benign	Adverse effects	Benign
Cost/kW	$100 - $300	$1000	$400
Round trip efficiency	85-90%	70-85%	>70%

In its new “Energy Darwinism” report, the investment bank Citi described energy storage as “likely to be the next solar boom” [32]. In his analysis of the Citi report, Giles Parkinson states that “the main driver of this investment will not be just to make renewables cost competitive, because they already are in many markets–but for the need to balance supply and demand” [33]. Citi also predicts that, if storage is the next solar boom and becomes largely adopted in markets such as Germany, the electricity load curves could change radically disrupting the fuel markets and causing more uncertainty for utilities [32].

To illustrate the effect of storage in a grid that combines both solar and wind power, Giles Parkinson, in his article, "Why the Hot Money Is Chasing Energy Storage," used the profile content in Figure 7 from the Citi report. This article describes the evolution of base load generation on sunny days in Germany with high solar production, with and without storage. Without storage, the base load—usually provided by coal, nuclear, diesel and gas—varies from about 3 to 25 GW within a day. To compensate this change in base load, gas generators are widely used because of their response time; although gas is expensive and gas-fired generators are being discontinued.

With storage, the base load is reduced and becomes fairly consistent. The flexible gas is no longer needed as before. Storage allows solar to initially shift peak demand from gas, then at higher penetration rates to reduce the contribution of base load producers (nuclear and coal).

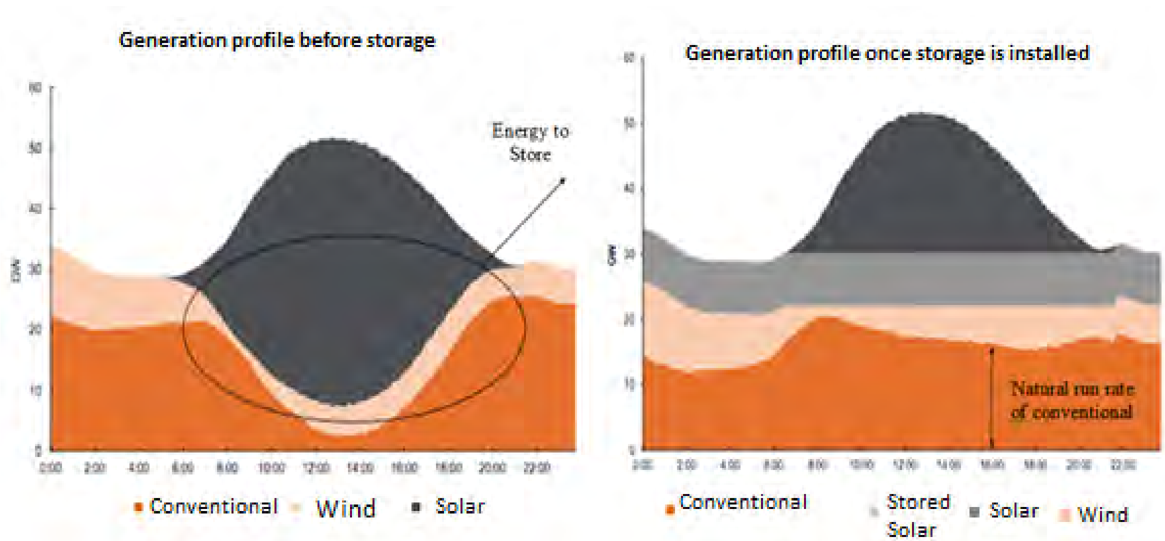

Figure 7. Effect of energy storage on the generation profile of an HRES (from [32])

Storage represents a good approach to reduce the issue of production intermittence and variability, especially in the case of an isolated hybrid electric grid (IHEG) also called isolated hybrid renewable energy system (IHRES) or an "island grid," that cannot be connected to a commercial electric grid. In the case of a hybrid electric grid (HEG), or hybrid renewable energy system (HRES) where the microgrid can be connected to the commercial grid, any excess production can be sold to the grid, and during low production periods, electricity can be purchased from the grid. However, an extra cost will usually be incurred due to the difference in electricity price, which is relatively more expensive when the wind speed is low.

The integration of power storage in an IHEG and the use of both PV solar power and wind power within the same grid offer new possibilities for the efficiency of the grid. Nonetheless, the variation of renewable energy production is still large enough that is unsafe to rely completely on renewable resources even when they are capable of satisfying the peak power demand. An abrupt drop in production cannot be remedied immediately by turning on back-up generators, as these require a warm-up period before they can contribute power. This delay in response is longer for diesel generators than for gasoline generators and gas generators. The ordinary solution that is adopted in an IHEG is to keep back-up generators running without any load so that they may be connected to the grid as needed. Even if this solution is safe and technically easy to implement, the cost incurred is very high both monetarily and in terms of GHG emissions.

D. THESIS CONTRIBUTIONS AND OUTLINE

A key component of a HRES is the energy management center (EMC). The role of the EMC is to control fuel-based generators and energy storage systems (ESS) optimally to meet demand at minimum cost. Thus, the EMC acts as a mediator between a facility's load side, generation side, and energy storage system (see Figure 8).

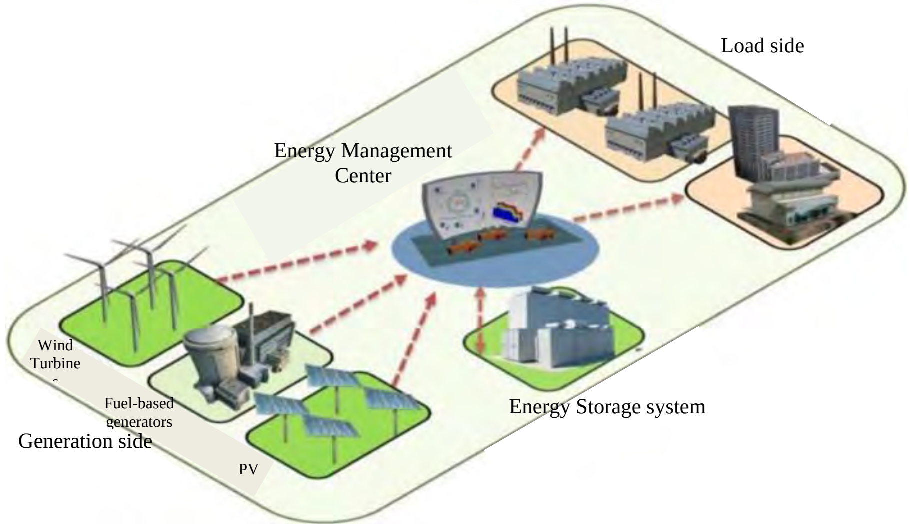

Figure 8. Scheme of an HEG with centralized energy management and energy storage (from [34])

This study aims to help the EMC to effectively and economically control the elements of the grid by anticipating the variations of the RES power production. Chapter II presents a literature review of a variety of approaches and studies conducted in the optimization of an EMC that controls HEG. Chapter III describes the mathematical formulation designed to address this problem. This model is tested in Chapter IV using various grid configurations, weather forecasts and demand scenarios. Finally, Chapter V evaluates the results found in Chapter IV and suggests further work and analyses.

II. LITERATURE REVIEW AND PROBLEM STATEMENT

The concept of optimizing an HEG is a recent research topic that emerged after new technologies, and the energy market made RES a competitive alternative to traditional fuel-based generators. The majority of studies done on HEG management and optimization were undertaken since 2006. Many new terms and concepts, such as “unit commitment,” “economic dispatch,” and “energy management system,” have been recently defined. The common goal of these concepts is the efficient control of electricity in terms of stability and operating cost. The unit commitment problem involves the scheduling of on/off status of the dispatchable generation units over a daily or weekly time horizon, while the economic dispatch problem focuses on the control of the generation units committed by the unit commitment problem over shorter time horizons.

A review of the research done concerning HEG modeling and optimization reveals the diversity of approaches deployed and creativity in the representation of uncertainties. The analysis of HEG is a broad field with connections over many branches, such as meteorology, energy marketing, electrical and power engineering. We focus in this literature review on the optimization of the HEG in terms of design and operating policy that tangentially combine all the branches cited previously.

A. LITERATURE REVIEW

Handschin, Neise, Neumann, and Schutz [35] create a mathematical model of a microgrid that includes different dispersed generation units including: gas generators; wind turbines; and hydroelectric power. The microgrid modeled is simultaneously producing thermal and electrical energy. Their study’s goal is to establish an optimal configuration of the grid that would minimize the operating cost. Initially, the study considers a deterministic model. Later, it includes uncertainties of renewable energy production and uncertainties of electricity and heat demand of customers. The study proves the ability of a decomposition algorithm to handle substantial problem elements and provide reasonable solutions.

Alexiadis, Dokopoulos, Sahsamanoglou, and Manousaridis [36] study many approaches for short-term forecasting of wind speed and the related wind power. They suggest various models based on artificial intelligence and spatial relations of wind speed. For the first model type, it is proven that artificial neural networks provide better results than an autoregressive moving average technique. For spatial correlation models, the authors suggest a new model, the *Spatial Correlation Predictor*, which they prove to be better than models using cross-correlation curves. The two types of models are tested using historic wind data collected over a seven-year period.

Sobu and Wu [37] make an approach to the optimal scheduling for an IHRES that integrates wind turbines and PV solar panels, as well as diesel generators as the stable power source and batteries for energy storage. The study uses stochastic scenarios of wind speed, solar radiation and power demand. The stochastic scenarios are generated by observing data, and analyzing mean-values and standard deviations. The problem is formulated as a stochastic minimization of the operation cost that is solved by a modern meta-heuristic technique known as particle swarm optimization [38]. This technique has been applied before in various combination optimization problems, such as the microgrid online control by Hayashi, Miyamoto, Matsuki, Iizuka, and Azuma [39], and unit commitment by Ting, Rao, and Loo [40]. The study by Sobu and Wu provides a stable operation schedule that includes uncertainties and an economic operation schedule for the deterministic model.

Bansal, Saini, and Khatod [41] use the evolutionary programming technique to establish an optimal daily scheduling of a wind-diesel system with battery storage facilities. The objective of the model was to maximize the profit from selling excess power production to the electricity market. Evolutionary programming is chosen because, according to the authors, it “does not require any information about derivatives to initialize and it generates population randomly. This makes this technique easy to apply, but the random population generation makes it time consuming” [41].

Eghbal, Kumar Saha, and Mahmoudi-Kohan [42] create a model for an IHEG that uses only geothermal, solar, and diesel generators as sources of electric power. They tried to use forecasted and available generation sources, battery storage, and demand response resources optimally to determine the most economic and reliable day-ahead generation scheduling for the IHRES. The study uses the comprehensive load economic model developed by Aalami, Moghadam, and Yosefi [43] to evaluate the impact of different demand response programs (DRPs) on the customer's load curve. DRPs are programs that seek to modify the load curve and shift the demand from peak hours to off-peak hours by changing incentives and prices. The study concludes that the "forecasted load curve can be modified using DRPs in such a way that load shedding is mitigated and battery storage is utilized efficiently" [42].

Lombardi, Sokolnikova, Suslov, and Styczynski [34] studied the optimal storage capacity that allows the minimum operating cost of an IHRES with different configurations. The IHRES studied includes four conventional diesel generators, a wind farm, and a PV plant. The grid is optimally scheduled by an intelligent EMC that schedules the fuel-based generators according to the load demanded. The EMS can also control the loads; if the grid is unable to satisfy the total demand, the EMS curtails a part of the load. It is shown that the storage becomes profitable if at least 10% of the annual electricity is produced by RES. The authors did some sensitivity analysis on the optimal storage capacity by varying the fraction of wind power and PV power from the total RES production as follows: only wind power, an equal proportion of wind power and PV power and only PV power. The optimal energy storage capacities needed were 57 Mwh, 22.8 Mwh, and 17 Mwh, respectively. The study concludes that the optimal storage depends on three factors: amount of energy generated by RES, type of RES technology used and the value of lost load used to estimate the costs due to the switch off of the loads.

The studies discussed in this section demonstrate the ability of mathematical models to control microgrids efficiently and economically, and even to determine their optimal configuration. The uncertainties were introduced in some studies either to represent load variability or RES production intermittence. The main objective of the studies was either to minimize operating cost or to maximize efficiency of the microgrid. Techniques used to solve the optimization problem were different, such as linear and non-linear deterministic optimization models, stochastic models, evolutionary programming, artificial neural networks, and meta-heuristic particle swarm optimization.

While the studies discussed have accurately represented the HRES or IHRES with mathematical models, they did not suggest a reasonable way to eliminate or anticipate the uncertainty of production from RES. The operating schedule determines only what generator to use at a particular time, but it does not provide a simple and clear instruction to the operator about what level or rotation speed to set the controllable generators. This thesis aims to address this issue.

III. PROBLEM FORMULATION

This thesis formulates an optimization model capable of using weather forecasts that predict the near-term output of renewable energy sources to determine optimal operating schedules for fuel-based generators. To accomplish this, we mathematically formulate how an EMC works. The laws of physics and the technical constraints that regulate the electric grid are included in our model. We also address the uncertainties of RES production by formulating a scenario-robust optimization model.

We also exercise this model in a variety of settings. We focus on HRES with different configurations:

- in grid-connected mode or in isolated mode (referred to as an IHRES)
- where energy storage (henceforth referred to as a “battery” or “batteries”) is present or absent

These various configurations will help to evaluate the importance of each element of the HRES separately and see how each element influences the total operating cost. A schematic diagram of two of our configurations appears in Figure 9.

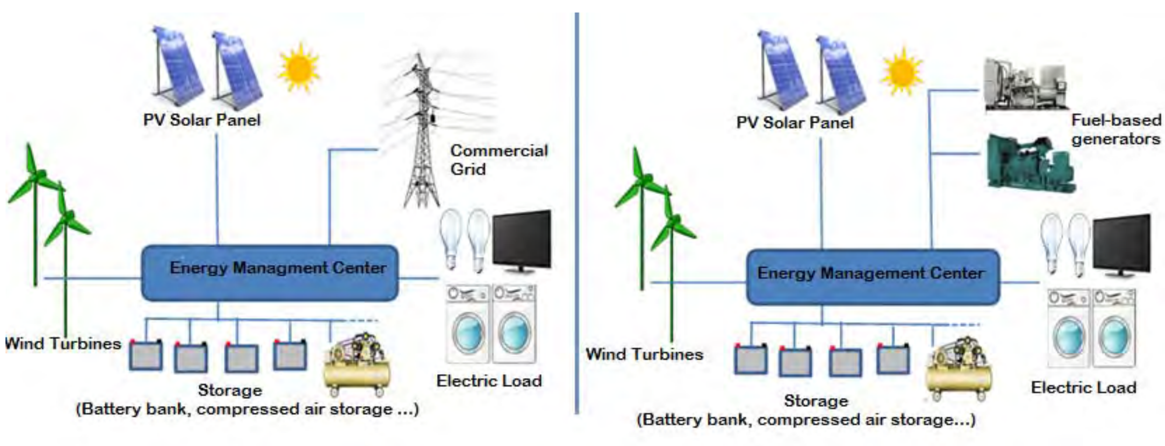

Figure 9. Configuration of an HRES (left) and IHRES (right) with energy storage

For an IHRES with ES, the schedule will define:

- when to turn a particular generator off or on and at what speed
- when to schedule a charge or discharge of the energy storage and at what rate

For a grid-connected HRES with dispatchable generator, in addition to the parameters defined in an IHRES schedule, the connected HRES schedule will also define:

- when and how much energy to buy from the grid
- and when and how much energy to sell to the grid.

For this type of scheduling, at least a day-ahead prediction is required. For better control of the HEG, the interval between two predictions should be as short as possible. For control of generators and batteries a time step of the length of thirty minutes or an hour is generally sufficient. However, the most precise interval that we can get from our meteorological model is a three-hour interval with an update of predictions every twelve hours; thus we interpolate the forecasts at each hour and we assumed that wind will not change within a particular hour interval. To mitigate the uncertainties in the weather forecast, we will analyze how the operating schedule and the total cost will vary when we try to satisfy the microgrid constraints based on multiple weather forecasts.

A. MODEL COMPOSITION AND TECHNICAL CHARACTERISTICS

The microgrid modeled in this study is composed of:

- One PV solar plant
- Ten wind turbines
- Three fuel-based generators
- One battery with characteristics similar to those of a compressed air energy storage or pumped-hydroelectric energy storage system.

1. Wind Turbines

Wind turbines convert the kinetic energy of the wind into mechanical energy and then into electricity. In order to capture the kinetic energy of the moving particles of air, the blades of the turbine should face the upcoming wind with an angle β called the *angle of attack* that causes the rotation. The majority of wind turbines have yawing mechanism that will control the entire nacelle to rotate into the wind with an optimal angle β. The yawing mechanism can be passive, like a tail vane on smaller wind turbines, or active with wind direction sensors and motors that rotate the nacelle.

For that reason, the direction of wind is not required to compute the power generated by the wind turbine. The real power output of a wind turbine is represented by the power curve which features three key wind speeds:

- Cut in wind speed V_{ci}: minimum wind speed required so that the wind turbine starts generating power. Typical cut-in wind speeds are between 3–5 m/s.
- Rated (nominal) wind speed V_n: This is the lowest speed at which the wind turbine reaches its rated (nominal) power output**.** Above this speed the rotor is controlled to maintain a constant power to limit loads and stresses on the blades**.**
- Cut-out wind speed V_{co}: This is the highest wind speed at which the turbine will operate. Above this speed it is unsafe to operate the turbine, so it is stopped.

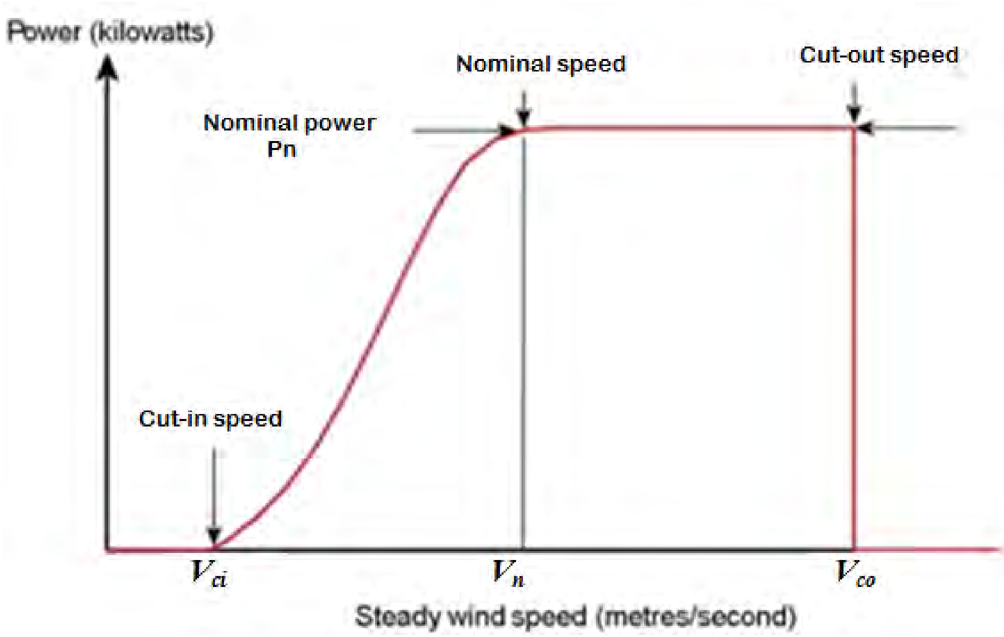

Figure 10. Typical wind turbine power curve with steady wind speed

As a function of wind speed, the power output of each wind turbine is modeled with respect to its typical power curve. The mathematical expression of the wind turbine power output $WindP(V)$ in kilowatts (kW) is expressed by Equation 1 in terms of the nominal power P_n in (kW), the cut-in wind speed V_{ci}, the cut-out wind speed V_{co}, and the nominal wind speed V_n [41].

$$WindP(V) = \begin{cases} 0 & , \quad V < V_{ci} \\ \dfrac{P_n}{(V_n^3 - V_{ci}^3)} V^3 - \dfrac{V_{ci}^3}{(V_n^3 - V_{ci}^3)} P_n & , \quad V_{ci} < V < V_n \\ P_n & , \quad V_n < V < V_{co} \\ 0 & , \quad V > V_{co} \end{cases} \qquad \text{(Eq. 1)}$$

2. PV Solar Panels

A PV solar panel is composed of modules or photovoltaic cells that convert light into electric current. The first solar cell was the crystalline silicon solar cell, which was invented in 1954. Its efficiency as mass produced is 14–20% [45]. To date, it is still widely used because of its competitive cost and long life. It accounts for more than 80% of the solar cell market. The CdTe-CdS thin film solar cells came second in the solar cell market (15%), with typical efficiency around 10% but cheaper cost [45].

The instantaneous power output of a PV array depends on the efficiency of the solar cells used, amount of insolation received by the cells (which is governed by the panel’s latitude, orientation of the panel, sky coverage, etc.), and the internal temperature of the cell. The power output of a PV array slightly decreases with its internal temperature. In our model we will assume that the power output of a particular PV panel depends only on insolation. A sample of a typical insolation is presented in Figure 11. However, in the study we used notional insolation forecast to compute the solar power generated by the PV panels.

Chen and Liu [44] expressed the PV power over a given time period, $SolarPower$, in terms of the insolation received during that period $Insolation$, the standard insolation $Insolation_{standard}$, the derating factor f_{PV} and the PV capacity Y_{PV} as:

$$SolarPower = f_{PV} Y_{PV} \left(\frac{Insolation}{Insolation_{standard}} \right) \qquad \text{(Eq. 2)}$$

The standard insolation $Insolation_{standard}$ is the standard amount of insolation used to evaluate the capacity of a PV module. A simpler and commonly-used equation involving only insolation, the total efficiency of the cells used $solarEfficiency$, and the total area of the panels $PanelSurface$ is:

$$SolarPower = solarEfficiency \times PanelSurface \times Insolation \qquad \text{(Eq. 3)}$$

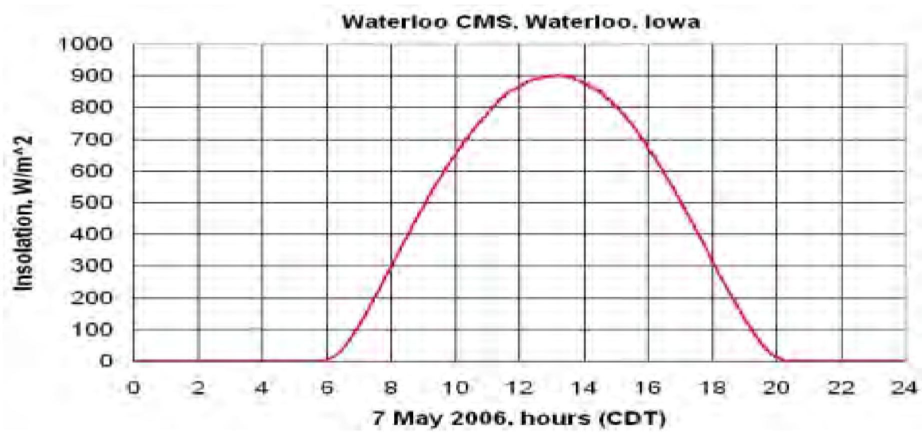

Figure 11. Sample of daily insolation

Table 3 presents some of the most commercialized PV cells and provides a comparison between them in terms of efficiency, cost, and market share.

Table 3. Comparison of most commercialized PV cells (from [45])

Type	**Efficiency (%)**	**Cost ($/watt capacity)**	**Market share (%)**
Monocrystalline Si	17-20	3.0	30
Polycristalline Si	15-18	2.0	40
Amouphous Si	5-10	1.0	5
CIGS	11-13	1.5	5
CdTe-CdS	9-13	1.5	10

3. Fuel-based Generators

Generators using diesel or gas are used as backup generators in case of disruption of the grid or as a main electric generator in an isolated grid such as on a forward operating base or an island. There are different sizes of generators with power outputs ranging from less than one hundred kilowatts to some thousands of kilowatts. A particular generator is designed to produce a specific power at a specific voltage and frequency. The power generated can be slightly regulated within the output limits by changing the rotation speed. This power output (P_{output}) is very nearly proportional to the rotations per minute squared (RPM^2) within the operating range. The coefficient of proportionality is called the production coefficient and it is denoted by $ProdCoef$:

$$P_{output} = ProdCoef \times RPM^2 \qquad \text{(Eq. 4)}$$

Similarly, the fuel consumption ($Fuel_{consumption}$) is proportional to the power output as shown in Figure 13 and by consequence proportional to the rotation speed squared:

$$Fuel_{consumption} = C_{cons} \times RPM^2 \qquad \text{(Eq. 5)}$$

In this thesis, we choose the production coefficient $ProdCoef$ and the fuel consumption coefficient C_{cons} such that the power production and the fuel consumption are similar to those of actual generators.

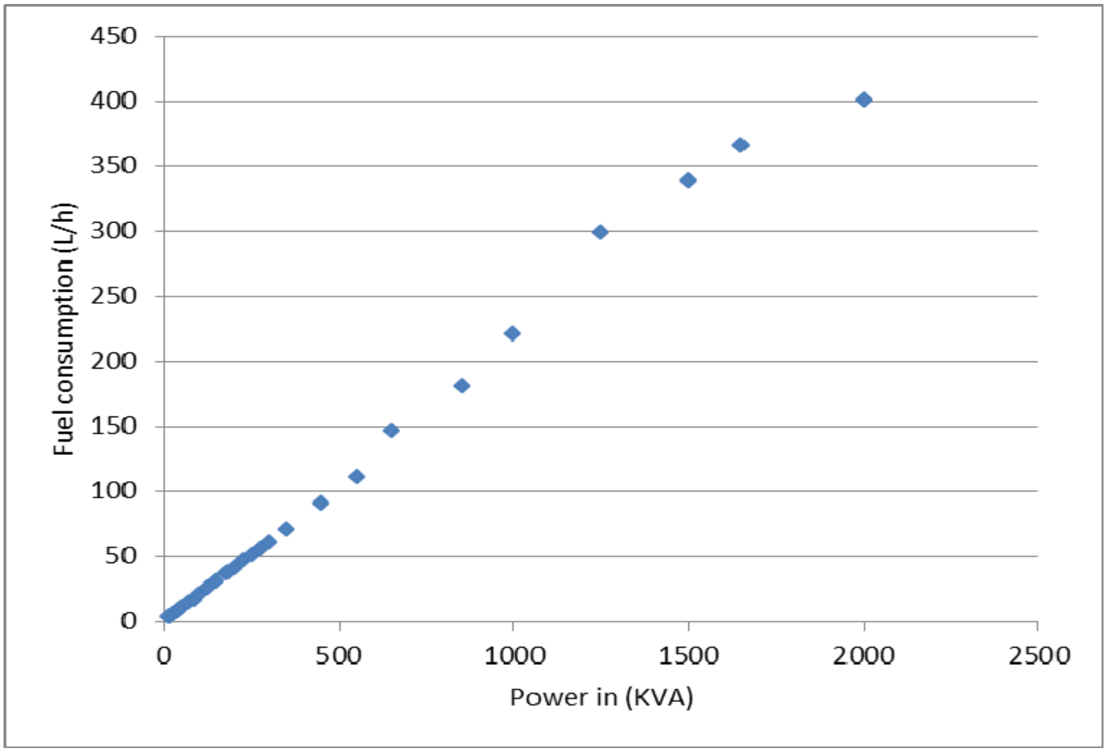

Figure 12. Fuel consumption of a diesel generator as a function of power output (from [46])

We use the squared rotation speed as a decision variable for our model in order to control the fuel-based power generation at any time step. This method is representative of the real functioning of generators and provides clear directives for the operator. Some models, such as that in [47], use a simpler representation of generators by considering just two states (On or Off).

Our model also sets a mandatory warm-up period during which the generator is running without contributing to the total power production. This reflects the generator's starting cost and also the time needed to stabilize the power output before coupling it to the grid.

4. Energy Storage

An energy storage mechanism is characterized by its efficiency, which is the fraction of energy recuperated from the total energy input. It is also characterized by its maximum storage capacity and minimum and maximum rates of charge and discharge. Gupta, Saini, and Sharma [48] modeled the state of charge B_k at time step *k* of a battery that has a charging and discharging efficiencies η_c and η_d respectively as

$$B_k = B_{k-1} + (P_{charge}\eta_c - \frac{P_{discharge}}{\eta_d}) \qquad \text{(Eq. 6)}$$

where P_{charge} and $P_{discharge}$ are respectively the power input for charging and the power output while discharging the battery. In this thesis, we consider just one measure of efficiency: the round trip efficiency. We choose this value so as to represent a realistic storage system. The state of charge of the battery at time step *k* B_k is represented in terms of the initial charge B_0, the round trip efficiency (1- α), and the power used for charging and discharging, P_{charge_k} and $P_{discharge_k}$, respectively.

$$B_k = B_0 + \sum_{k' \le k} ((1-\alpha) \times P_{charge_{k'}} - P_{discharge_{k'}}) \qquad \text{(Eq. 7)}$$

5. Weather Forecasts

Weather forecasts can be generated from two different types of weather models: global models and regional models. Global models cover the whole earth and provide weather forecasts 1-2 weeks in the future. Regional models cover a limited area, generally have a higher horizontal and vertical resolution than global models, and are usually run for a few days. Two well-known regional models are the Fifth-Generation Penn State/NCAR Mesoscale Model MM5 and its successor the Weather Research and Forecasting (WRF) model, which is used for creating weather forecasts and climate predictions. The forecasts used in our analysis were provided by the Meteorology Department at the Naval Postgraduate School, which used a WRF model. GFS and WRF models are both run operationally by the National Oceanic and Atmospheric

Administration. The Naval Research Laboratory in Monterey, CA also provided us with forecast data used for development purposes; this data was generated by Global Forecast System (GFS), which is a global model.

Although weather predictions are typically published as a single forecast, this forecast is constructed based on a collection of possible forecasts produced as output by a weather model. This collection, known as an ensemble of forecasts, is of particular interest in planning problems due to the fact that each ensemble member represents a plausible future outcome. In many applications, the desire to obtain a robust solution necessitates consideration of multiple possible outcomes. For applications in which the primary uncertainty is due to weather, such as the one considered in this thesis, an ensemble of forecasts represents an ideal means for performing robust optimization. Thus, the model developed in this thesis optimizes over an ensemble of forecasts, henceforth referred to as forecast scenarios $s \in S$.

B. PROBLEM FORMULATION

We now present our mathematical model, which determines the optimal schedule in which to run fuel-based generators in a hybrid electric grid in order to satisfy energy demand while minimizing operating costs.

1. Sets

$g \in G$	Fuel-based generators
$w \in W$	Wind turbines
$b \in B$	Batteries
$k \in K$	Time steps
$s \in S$	Weather forecast scenarios

2. Scalars and Parameters

List of Scalars [Units]

$deltaT$	Duration of time step [hours]
$Nmax$	Maximum tolerable number of changes in the generator's speed during the planning horizon

List of Parameters

$ProdCoef_g$	Production coefficient of generator g [kW/RPM^2]
$ProdCost_g$	Production cost coefficient of generator g [\$/kWh]
$InitialRPM2_g$	Initial squared rpm of generator g [RPM^2]
$InitialContrib_g$	Contribution status of generators at initial step [binary]
$MaxRPM2_g$	Maximum squared RPM of running the generator g [RPM^2]
$MinRPM2_g$	Minimum speed of running the generator g [RPM^2]
$warmup_g$	Number of time steps generator g must run before it can contribute power
$Demand_k$	Electricity demand at time step k [kW]
$WindP_{w,k,s}$	Wind power generated by wind turbine w at time step k from wind forecast scenario s [kW]
$PurchaseCost_k$	Cost of purchasing power from the commercial grid at time step k [\$/kWh]
$SellingPrice_k$	Revenue from selling power to the commercial grid at time step k [\$/kWh]
$SolarPower_{k,s}$	Power generated by the PV solar panels at time step k from insolation forecast scenario s [kW]
$MaxCharge_b$	Maximum rate of charging battery b [kW]
$MinCharge_b$	Minimum rate of charging battery b [kW]
$MaxDischarge_b$	Maximum rate of discharging battery b [kW]
$MaxCapacity_b$	Maximum storage capacity of battery b [kWh]

α_b	Fraction of power lost while charging battery *b* (loss factor)
$InitialStorage_b$	Initial energy stored in battery *b* [kWh]
$StorageCost_b$	Cost of storing electricity in battery *b* [$/kWh]

3. Decision Variables

$ON_{g,k}$	Binary Equals 1 if generator *g* is running at time step *k* and 0 otherwise
$RPM2_{g,k}$	Continuous (≥0)Squared rotation speed [RPM^2]
$CONTRIB_{g,k}$	Binary Contribution status of generator *g* at time step *k*
$PCONTRIB_{g,k}$	Continuous (≥0) Power contributed by generator *g* at time step *k* [kW]
$PBUY_k$	Continuous (≥0) Power purchased from the grid at time step *k* [kW]
$PSELL_k$	Continuous (≥0) Power sold to the grid at time step *k* [kW]
$PCHARGE_{b,k,s}$	Continuous (≥0) Rate of charging battery *b* at time step *k* [kW]
$PDCHARGE_{b,k,s}$	Continuous (≥0) Rate of discharging battery *b* at time step *k* [kW] $CHARGE_{b,k,s}$ Binary Equals 1 if battery *b* will be charged at time step *k* in scenario *s* and 0 otherwise
$DCHARGE_{b,k,s}$	Binary Equals 1 if battery *b* will be discharged at time step *k* in scenario *s* and 0 otherwise
$CHANGE_{g,k}$	Binary Equals 1 if there is a change in generator *g*'s speed at step *k* and 0 otherwise

4. Objective Function

The ultimate goal of the optimization model is to minimize the operating cost of the hybrid electric grid for the next 24 hours. The total cost includes the production cost by fuel-based generators, the total cost of power purchased from the commercial grid, the total cost of storing energy in the batteries. From the sum of all the previously mentioned costs we subtract the revenue from selling energy to the grid.

$$Min\,Z = \begin{bmatrix} \sum_k \sum_g ProdCost_g \times ProdCoef_g \times RPM2_{g,k} \times deltaT \\ + \quad \sum_k PurchaseCost_k \times PBUY_k \times deltaT \\ + \ \frac{1}{|S|} \ \sum_k \sum_b \sum_s StorageCost_b \times PCHARGE_{b,k,s} \times deltaT \\ - \quad \sum_k SellingPrice_k \times PSELL_k \times deltaT \end{bmatrix} \qquad \text{(Eq. 8)}$$

5. **Constraints**

The constraints are used to make our mathematical model coherent with physics laws and representative of energy system operations:

$$\sum_g PCONTRIB_{g,k} + \sum_w WindP_{w,k,s} + \sum_b PDCHARGE_{b,k,s} + SolarPower_{k,s} + PBUY_k$$
$$\geq \ PSELL_k + Demand_k + \sum_b \frac{PCHARGE_{b,k,s}}{1-\alpha_b} \qquad \forall \ k \in K,\ s \in S \qquad \text{(Eq. 9)}$$

$$PCONTRIB_{g,k} \leq \ MaxRPM2_g \times ProdCoef_g \times CONTRIB_{g,k} \qquad \forall k \in K,\ g \in G \qquad \text{(Eq. 10)}$$

$$PCONTRIB_{g,k} \geq \ ProdCoef_g \times RPM2_{g,k} - (1 - CONTRIB_{g,k}) \times MaxRPM2_g \times ProdCoef_g$$
$$\forall k \in K,\ g \in G \qquad \text{(Eq. 11)}$$

$$PCONTRIB_{g,k} \leq \ ProdCoef_g \times RPM2_{g,k} \qquad \forall k \in K,\ g \in G \qquad \text{(Eq. 12)}$$

$$CONTRIB_{g,k} \leq ON_{g,k'} \qquad \forall\ g,k,k' : k - warmup_g \leq k' \leq k \qquad \text{(Eq. 13)}$$

$$CONTRIB_{g,k} \leq InitialContrib_g \qquad \forall\ g,k : k \leq warmup_g \qquad \text{(Eq. 14)}$$

$$InitialStorage_b + \sum_{k' \leq k} (PCHARGE_{b,k',s} - PDCHARGE_{b,k',s}) \times deltaT \leq MaxCapacity_b$$
$$\forall\ b \in B,\ s \in S,\ k \in K \qquad \text{(Eq. 15)}$$

$$InitialStorage_b + \sum_{k' \le k} (PCHARGE_{b,k',s} - PDCHARGE_{b,k',s}) \times deltaT \ge 0 \quad \forall\ b \in B, k \in K,\ s \in S \qquad \text{(Eq. 16)}$$

$$PCHARGE_{b,k,s} \le MaxCharge_b \times CHARGE_{b,k,s} \quad \forall b \in B, k \in K,\ s \in S \qquad \text{(Eq. 17)}$$

$$PCHARGE_{b,k,s} \ge MinCharge_b \times CHARGE_{b,k,s} \quad \forall b \in B, k \in K,\ s \in S \qquad \text{(Eq. 18)}$$

$$PDCHARGE_{b,k,s} \le MaxDischarge_b \times DCHARGE_{b,k,s} \quad \forall b \in B, k \in K, s \in S \qquad \text{(Eq. 19)}$$

$$CHARGE_{b,k,s} + DCHARGE_{b,k,s} \le 1 \quad \forall b \in B, k \in K,\ s \in S \qquad \text{(Eq. 20)}$$

$$CHANGE_{g,k} \ge \left(\frac{1}{MaxRPM\,2_g}\right) \times [RMP2_{g,k} - RMP2_{g,k\text{-}1}] \quad \forall g \in G,\ k \in K \qquad \text{(Eq. 21)}$$

$$CHANGE_{g,k} \ge \left(\frac{1}{MaxRPM\,2_g}\right) \times [RMP2_{g,k-1} - RMP2_{g,k}] \quad \forall g \in G, k \in K \qquad \text{(Eq. 22)}$$

$$\sum_k CHANGE_{g,k} \le\ Nmax \quad \forall g \in G \qquad \text{(Eq. 23)}$$

$$RPM\,2_{g,k} \le MaxRPM\,2_g \times ON_{g,k} \quad \forall g \in G,\ k \in K \qquad \text{(Eq. 24)}$$

$$RPM\,2_{g,k} \ge MinRPM\,2_g \times ON_{g,k} \quad \forall g \in G,\ k \in K \qquad \text{(Eq. 25)}$$

$$ON_{g,k} \in \{0,1\} \quad \forall\ g \in G,\ k \in K \qquad \text{(Eq. 26)}$$

$$CONTRIB_{g,k} \in \{0,1\} \quad \forall\ g \in G,\ k \in K \qquad \text{(Eq. 27)}$$

$$CHARGE_{b,k,s} \in \{0,1\} \quad \forall b \in B, k \in K,\ s \in S \qquad \text{(Eq. 28)}$$

$$DCHARGE_{b,k,s} \in \{0,1\} \quad \forall b \in B, k \in K,\ s \in S \qquad \text{(Eq. 29)}$$

$$CHANGE_{g,k} \in \{0,1\} \quad \forall\ g \in G,\ k \in K \qquad \text{(Eq. 30)}$$

$$RPM\,2_{g,k} \ge 0 \quad \forall g \in G,\ k \in K \qquad \text{(Eq. 31)}$$

$$PCONTRIB_{g,k} \ge 0 \quad \forall k \in K,\ g \in G \qquad \text{(Eq. 32)}$$

$$PCHARGE_{b,k,s} \ge 0 \quad \forall b \in B, k \in K,\ s \in S \qquad \text{(Eq. 33)}$$

$$PDCHARGE_{b,k,s} \geq 0 \qquad \forall b \in B, k \in K,\ s \in S \qquad \text{(Eq. 34)}$$

$$PBUY_k \geq 0 \qquad \forall k \in K \qquad \text{(Eq. 35)}$$

$$PSELL_k \geq 0 \qquad \forall k \in K \qquad \text{(Eq. 36)}$$

- Equation 9 ensures that power production is high enough to satisfy demand at each time step *k* while accounting for power bought from or sold to the commercial grid as well as power used to charge the battery. $WindP_{w,k,s}$ is computed using Equation 1 and $SolarPower_{k,s}$ is computed using Equation 3. Note that the electricity purchased and sold do not vary by scenario. This can reflect, for instance, a contractual obligation to purchase or provide a certain planned amount of electricity. Future research may allow the electricity bought and sold to vary by scenario.

- Equations 10, 11 and 12 are used to model the power contributed by generator *g* at time step *k*. The power contibuted was initially defined as:

$$PCONTRIB_{g,k} = ProdCoef_g \times RPM2_{g,k} \times CONTRIB_{g,k} \qquad \forall g \in G,\ k \in K \qquad \text{(Eq. 37)}$$

However, Equation 37 is nonlinear because we multiply $RPM2_{g,k}$ by $CONTRIB_{g,k}$. In order to keep the model linear, we linearized this nonlinear equation using equations 10, 11 and 12.

- Equations 13 and 14 ensure that generator *g* does not contribute to power production at time step *k* unless it has been running sufficiently long or was contributing in its initial condition and has remained running since then.

- Equation 15 keeps track of the quantity of energy stored in every battery and forces it to be always less than the maximum storage capacity of the battery.

- Equation 16 ensures that the battery storage will not go below zero.

- Equations 17 and 18 enforce the maximum and the minimum rate of charging each battery.

- Equation 19 limits the maximum rate of discharging a battery.
- Equation 20 is used to ensure that we can not charge and discharge a battery *b* at the same time step *k*. This constraint was included in order to eliminate unrealistic behavior in problem instances with multiple optimal solutions.
- Equations 21, 22 and 23 calculate the number of changes in rotation speed for each generator and limit this number at most *Nmax*. This constraint is included to reflect real operational considerations.
- Equations 24 and 25 define respectively the maximum and the minimum values of the rotation speed squared (RPM^2) for each generator.
- Equtions 26-36 declare variable types.

Note that in order to model an isolated IHEG one may simply set $PBUY_k$ and $PSELL_k$ to zero for all *k*.

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IV. ANALYSIS OF RESULTS

In this chapter, we test the model formulated by optimizing various configurations of the HEG. The technical characteristics of the components of the model studied are represented in the first part of this chapter. We discuss and represent some optimal plans generated from the optimization model in order to justify the steps proposed by the solver.

We implemented our model using the General Algebraic Modeling System (GAMS) rev. 236 and solved it using CPLEX 12.2.0.2 on a Dell Latitude E6510 PC with a 2.53 GHz Intel Core i5 CPU and 4 GB of RAM. We will discuss the details of our problem instances in the following sections; however, our instances contained approximately 5,300 decision variables, of which approximately 1,400 were discrete, and 4,800 constraints. Typical solution times were 5-60 seconds.

A. MODEL INPUTS

1. Generators

We consider an HEG configuration with 3 different generators as shown in Table 4. Generator Gen1 can be considered as a diesel generator that has a high power production capability with a relatively inexpensive cost but a relatively long warm-up period.

Generator Gen2 has a shorter warm-up period, but it is slightly more expensive to run it than Gen1. Gen2 can be considered as a gas generator with a high production capacity ranging from 360 to 640 kW. Similarly, Generator Gen3 can be regarded as a smaller gas generator with a production capacity ranging from 250 to 360 kW.

Usually, when the electric grid does not include renewable sources, the diesel generator is used permanently to provide the base load while gas generators are used to compensate for variations in the load.

Table 4. Parameter input of the fuel-based generators modeled

g	$ProdCoef_g$ (kW/RPM^2)	$ProdCost_g$ ($/kWh)	$MinRPM2_g$	$MaxRPM2_g$	Min Power (kW)	Max Power (kW)	$warmup_g$ (hr)
Gen1	0.001	0.1	490000	640000	490	640	1
Gen2	0.001	0.12	360000	640000	360	640	0.5
Gen3	0.001	0.14	250000	360000	250	360	0.5

2. Turbines

We model two different types of wind turbines. Turbines 1 through 5 represent medium production scale turbines that are located in location A. Turbines 6 through 10 represent bigger wind turbines with a nominal production of 270 kW. The detailed characteristics of the turbines are presented in Table 5.

Table 5. Technical characteristics of the wind turbines modeled

	Cut-in speed V_{ci} (m/s)	Nominal speed V_n (m/s)	Cut out speed V_{co} (m/s)	Location	Nominal power P_n (kW)
Turbines 1,2,...,5	3	12	15	A	86.4
Turbines 6,7,…,10	4	15	18	B	270

3. Batteries

The model can include different types of storage techniques. For simplicity we consider only a single type of storage. Its characteristics appear in Table 6.

Table 6. Technical characteristics of the battery

	Max Charge / Discharge Rates (kW)	Max Capacity (kWh)	Loss Factor α	Initial charge (kWh)	Cost ($/kWh)
Battery	300 / 200	300	0.2	0	0.02

4. Commercial Grid

Military bases, even those located on foreign territory, can be connected to the commercial electric grid. In FOBs, the local price of electricity and the characteristics of the grid in terms of stability and invulnerability, in addition to other local factors, will define the fraction of power purchased from the grid. The EMC modeled can allow the HEG to be connected to the commercial grid either as an additional power supply source or as a customer that will purchase any excess power produced. Selling renewable energy to the grid is a new technique applied in many countries like the United Kingdom. In order to sell back power to the grid, the HEG should have net-metering systems that keep track of how much energy is used from the grid and how much self-generated power supplied to the commercial grid [49].

In general both selling and buying prices vary according to the electricity market, as shown in Figure 13. The electricity prices used in the analysis are notional; however their magnitudes are very close to the real prices in the U.S. electricity market. The average U.S. retail price of electricity in 2011 was about 0.12$/kWh [50].

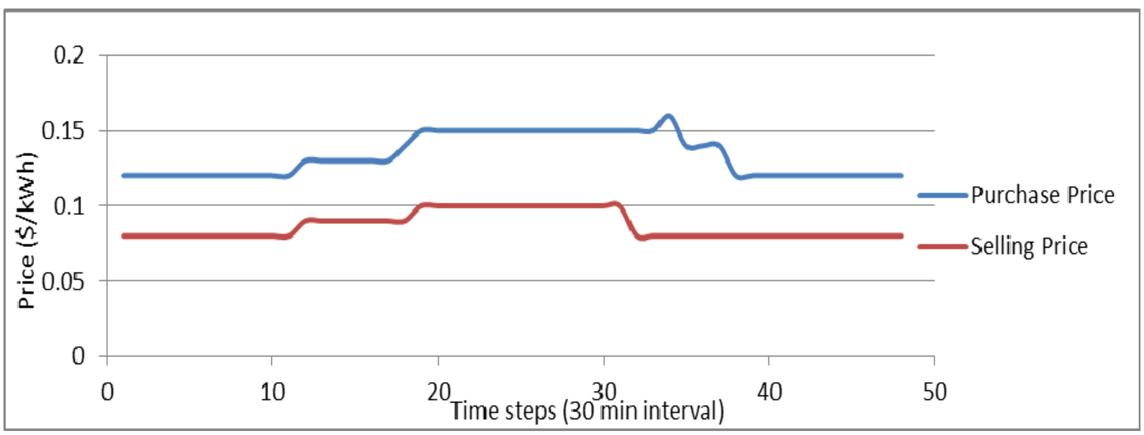

Figure 13. Variation of the market price of electricity ($/kWh) during a day period

5. Weather Forecast

a. Wind Forecast

The utility of the HEG operating plan generated by the model is mainly determined by the accuracy the weather forecast. For this analysis, we use weather forecast data provided by the Meteorology Department at the Naval Postgraduate School. These forecasts predict the wind speed at two different locations (A and B) near Naval Station Newport in Newport, RI, where a 9-MW wind farm is under implementation. Those two locations are presented in Figure 14.

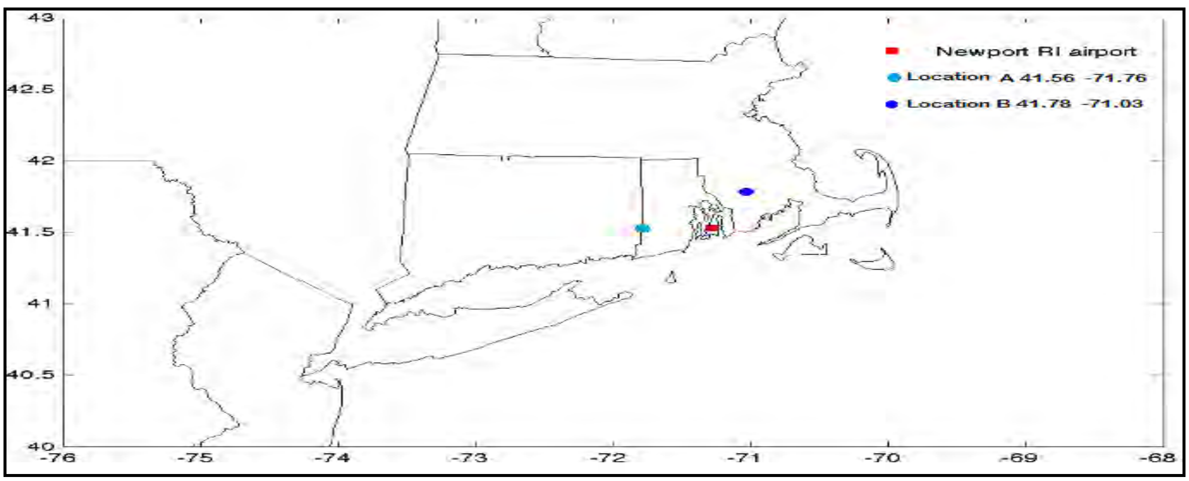

Figure 14. Geographic location of the two profile sites

Figures 15 and 16 represent a sample of wind speed forecasts in the two locations starting on November 1, 2008, at midnight. Each line represents the forecasted wind speed produced by a particular ensemble member (scenario), which we denote as S1, …,S10. The results show that during the first 5 to 6 hours, the predictions are very similar among all models. After that, the predictions diverge into two clusters: the first is composed of 6 models (S2, S3, S4, S6, S8 and S10) and the second of 4 models (S1, S5, S7, S9). The first cluster has more conservative predictions of the wind speed than the second. This behavior is typical and reflects the uncertainty inherent in weather predictions, as well as the fact that this uncertainty grows with time.

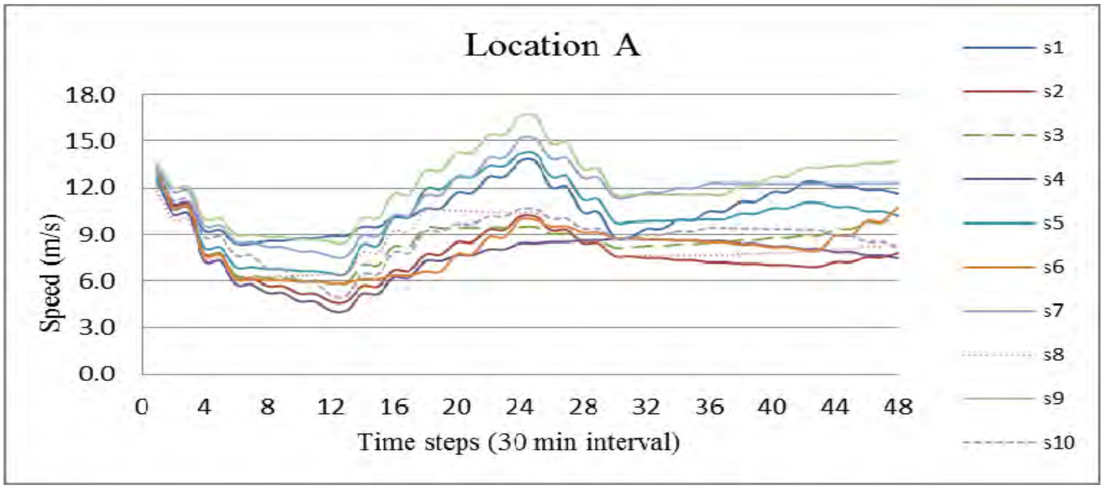

Figure 15. Different wind speed predictions at location A on 12/01/2008

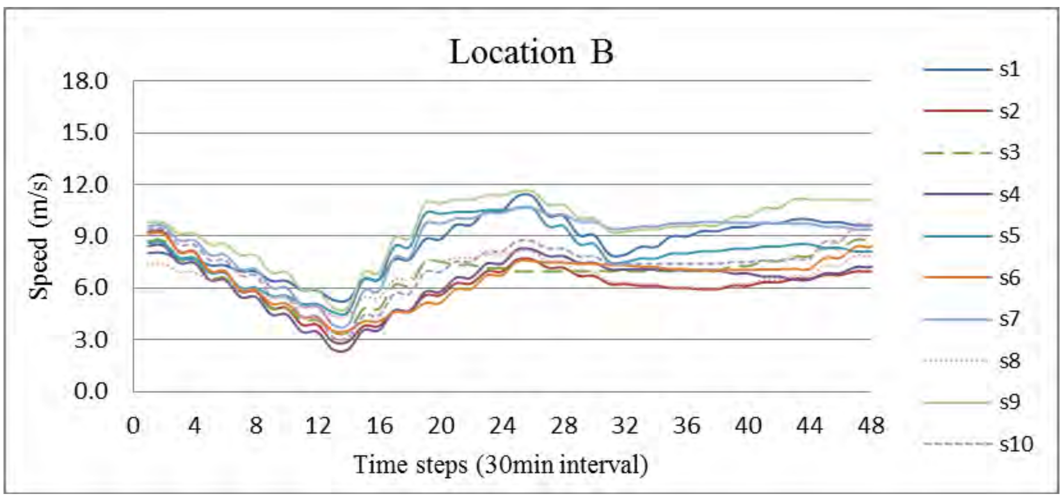

Figure 16. Different wind speed predictions at location B on 12/01/2008

b. Insolation Forecast

The WRF model discussed previously provides much information such that humidity and temperature that can be used to predict the formation of clouds and after that predict the insolation. The process is challenging for a non-meteorology specialist. Thus, the insolation forecasts used in our analysis are notional.

6. The Load

The thesis does not study the electric load or how to predict it. However, we conducted a preliminary analysis of a 5-year history of load data from the Defense

Language Institute Foreign Language Center (DLIFLC) in Monterey, California, and the Presidio of Monterey. Figures 17 and 18 present the variation of the daily load during the months of August and January, respectively. The historic load presents some consistent behavior that is slightly affected by the month of the year but very different between weekdays and weekends. The absence of strong correlation between load and month of the year can be explained by the moderate weather of Monterey, which does not require excessive heating or air-conditioning. The consistency of the load during the week can be explained by the consistency of the schedule of activities in the DLIFLC.

This can give more credibility and reliability to the results provided by the optimization model, even though it does not account for the variability of the load. To test the optimization model, a single load was used on August 8, 2008.

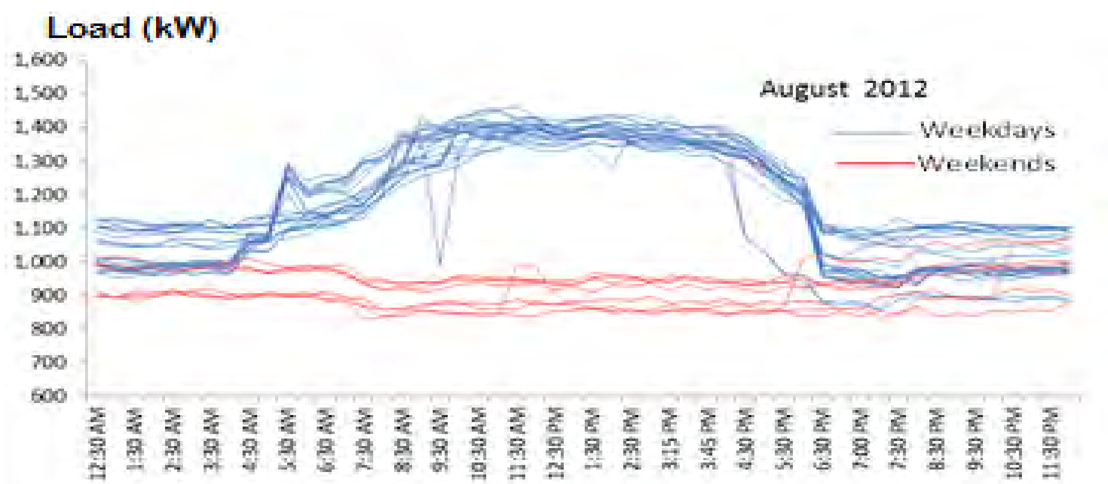

Figure 17. Daily electric load at DLIFLC during August 2012

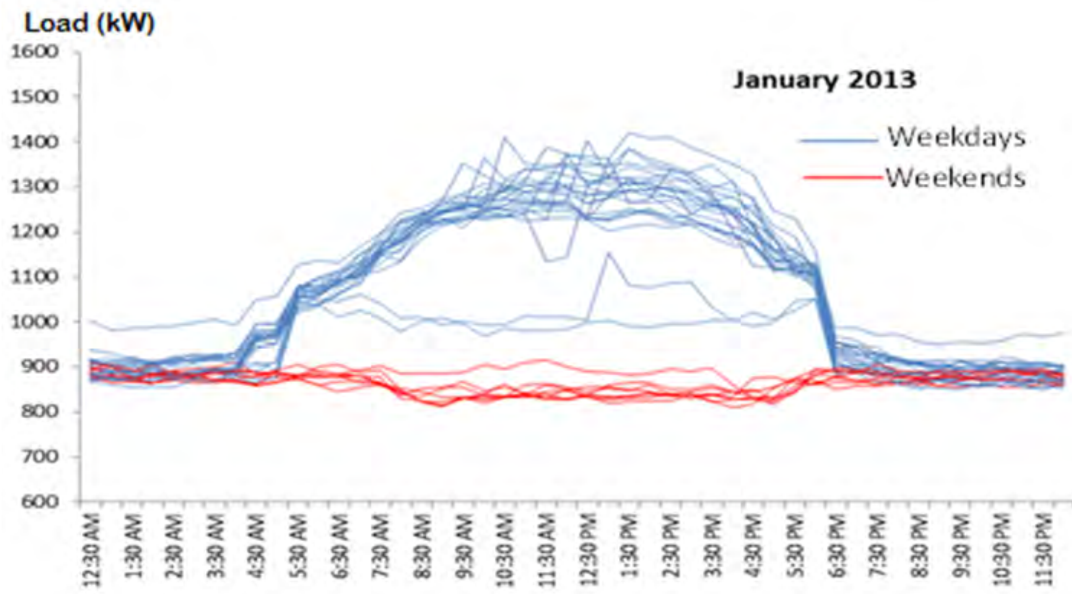

Figure 18. Daily electric load in kW at DLIFLC during January 2013

B. RESULTS FOR ISOLATED

In this section, we consider an IHEG with various configurations. First, we quantify the gain from integrating RES in our grid by running the model with and without energy storage. Next, we study the optimal schedule for the IHEG provided by different optimization methods. We analyze the optimal plan over weather forecast scenario S1, then over different scenarios, over a subset of scenarios simultaneously, over the average of scenario forecasts and finally over the average of renewable energy generated by all the scenarios.

1. Grid with Fuel-based Generators Only

a. Grid without Energy Storage

If we try to satisfy the daily demand using only the fuel-based generators, the total cost will be $3,069.46. The optimization model will simply choose to run at full speed the diesel-fueled generator that has the cheapest cost and provide the extra power needed using the other two gas generators.

b. Grid with Energy Storage

If we add the possibility of storing energy, the cost will slightly decrease and become \$3,056.94 instead of \$3,069.46. The quantity of energy stored is very limited. The power is stored when the amount of energy that we need from the gas generator (Gen2) is less than the minimum power production of that generator, which is 360 kW for this particular configuration. For the same reason, the model does not allow the use of the diesel generator (Gen1) at its maximum power in the last 6 hours. The optimal composition of the power supply and demand are presented in Figures 19 and 20, respectively.

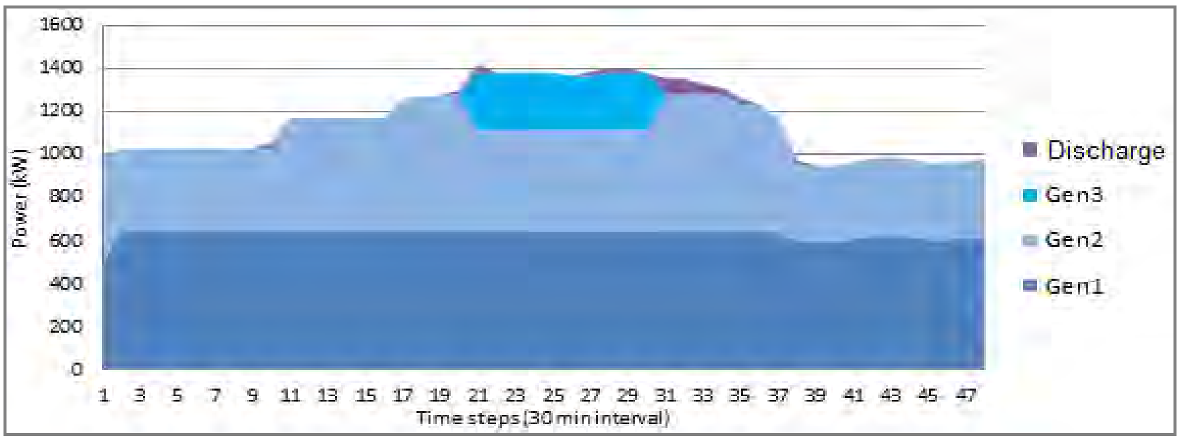

Figure 19. Composition of the total power generated for an isolated grid with energy storage but without RES

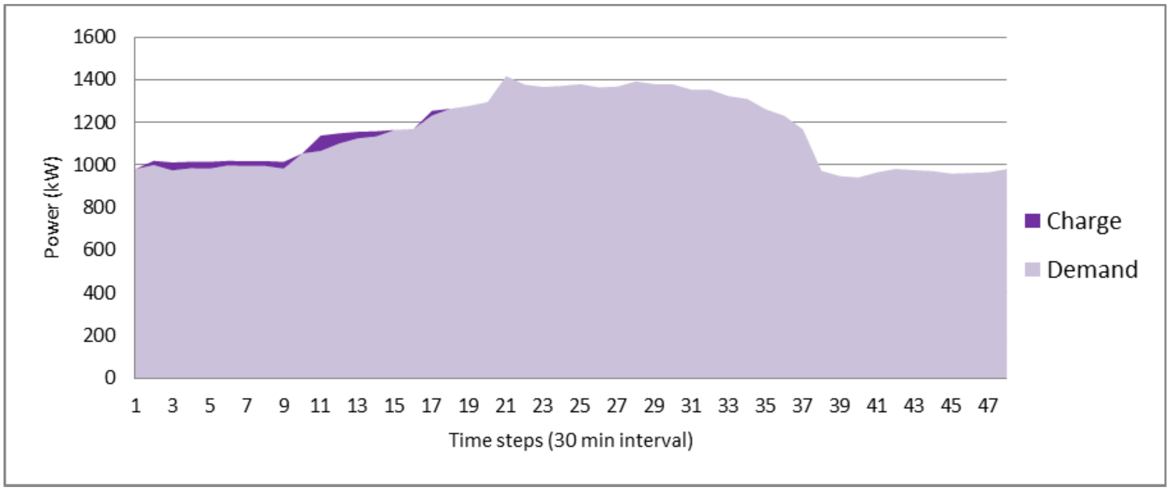

Figure 20. Composition of the total power demanded for an isolated grid with energy storage but without RES

From this simple configuration, we can notice the end-of-horizon effects: the optimization model tries to use up all the energy stored during the optimization period and does not account for the load of the following day by storing some energy. We will discuss a potential remedy for end-of-horizon effects in Section F.

2. Optimization of an IHEG over Forecast Scenario S1

In this part, we include both wind turbines and PV panels in the model. Initially, we will optimize the operating schedule over just one weather forecast scenario, S1.

a. IHEG without Storage

The wind speed used in the model is forecasted to increase around noon, which coincides nicely with the peak demand. Similarly, the PV power production peaks at the same time as the load.

The minimum total operating cost for the IHEG configuration without energy storage using scenario S1 $1,809.81. The integration of both wind and solar power helped to decrease the cost by 41%; however, this figure assumes that forecast scenario S1 is actually realized.

Although we assume that both the diesel generator (Gen1) and the high production gas generator (Gen2) are initially running, the optimal schedule requires that we turn off Gen2 and adjust Gen1 according to the variation of the load and the wind power during the first two hours. Later, when Gen1 and the wind turbines can no longer satisfy the load, the model chooses to turn on the smaller gas generator Gen3 when the deficit is less than the minimum power production of Gen2 and to use Gen2 otherwise.

Note that during the peak load only Gen1 is used, and it is not even used at its maximum capacity. This is because the peak load coincides with the peak of renewable energy production.

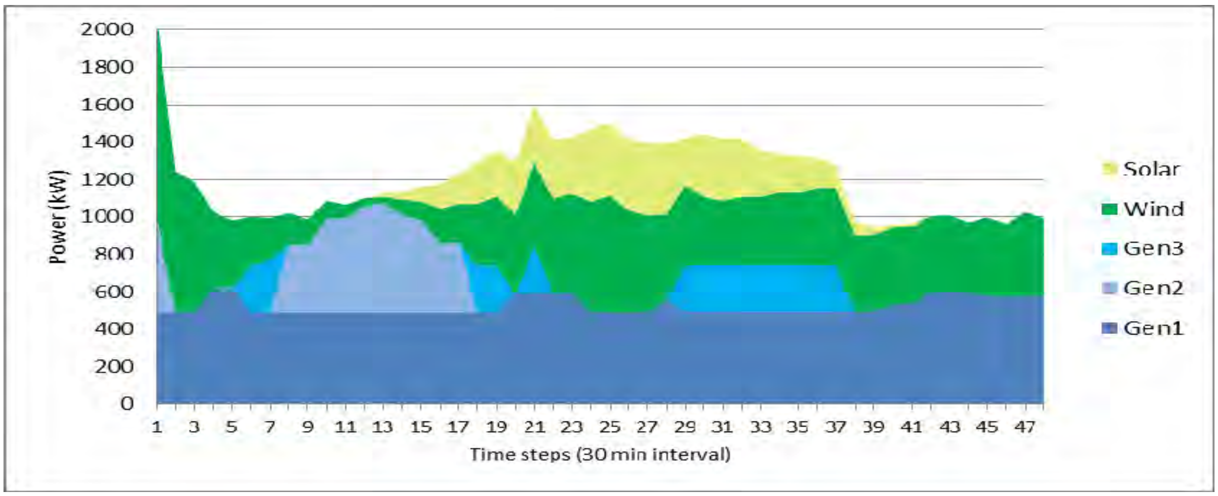

Figure 21. Optimal composition of the power supplied to the IHEG without ES when optimizing over weather forecast scenario S1

b. IHEG with Storage

Including storage has a clearer effect in this configuration. The total operating cost has decreased by about 9% ($1,645.86 with storage vs. $1,809.81 without storage). In addition to the reduction in the operating cost, the small gas generator Gen3 is not used at all during the optimization horizon considered. The small shortfalls in power that were previously satisfied by Gen2 are now satisfied by discharging the battery.

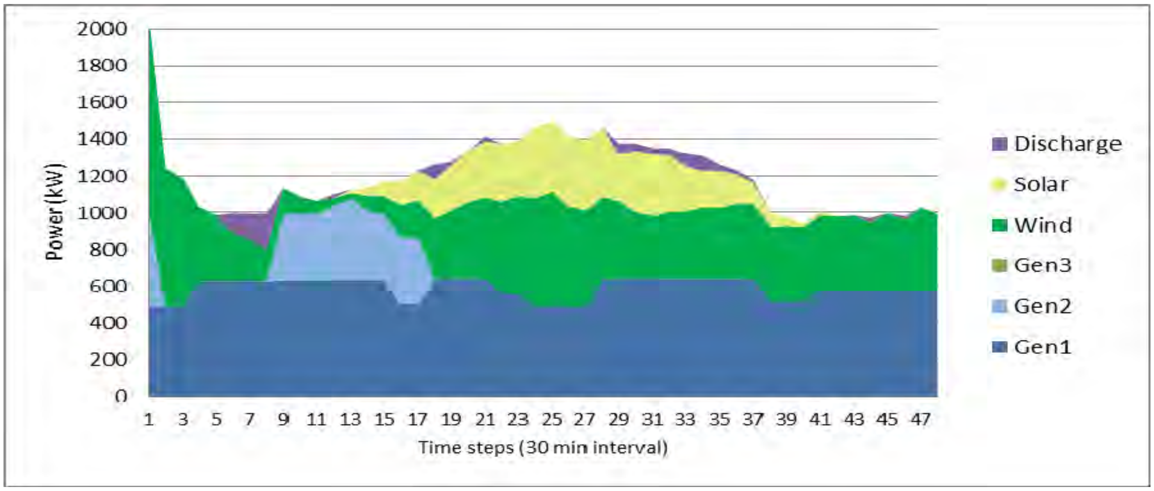

Figure 22. Optimal composition of the power supplied to the IHEG with ES

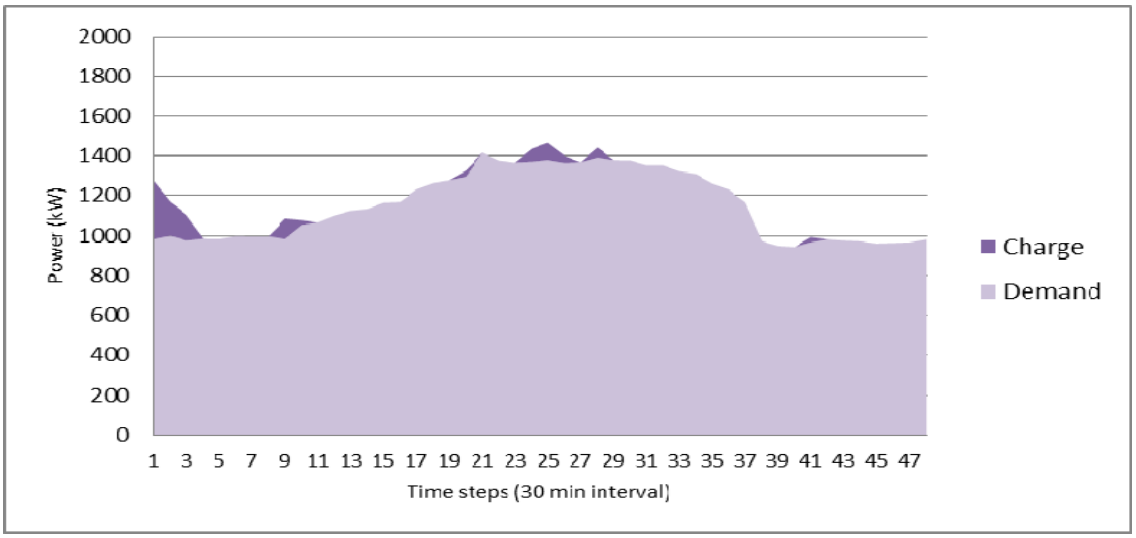

Figure 23. Composition of the load for the IHEG with ES

3. Optimization over Different Forecast Scenarios

All weather forecasts have some error of prediction, which can greatly influence the quality of the operating plan and threaten the stability of the grid. To minimize the risk that can result from using an inaccurate weather forecast, we suggest optimizing over multiple scenarios at the same time. Before optimizing over multiple scenarios, however, we analyze how the optimal schedule and the operating cost will change from one scenario to another. Figures 24 and 25 present respectively the wind power and the solar power production resulting from the 10 different weather scenarios. The wind power output has a behavior similar to the wind speed forecasted but not totally identical because the wind power is not exactly proportional to the wind speed. Rather, it is proportional to the wind speed cubed, and it also exhibits saturation effects.

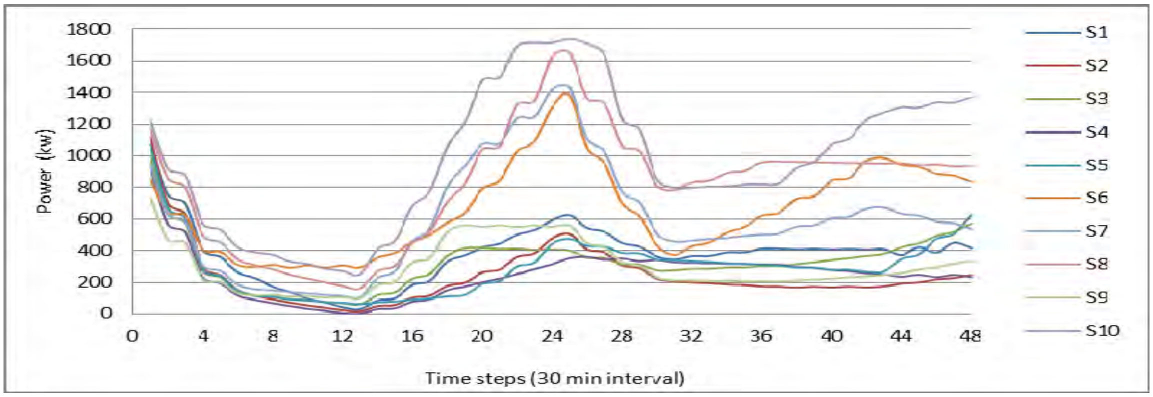

Figure 24. Potential wind power generated from the 10 different weather forecast scenarios

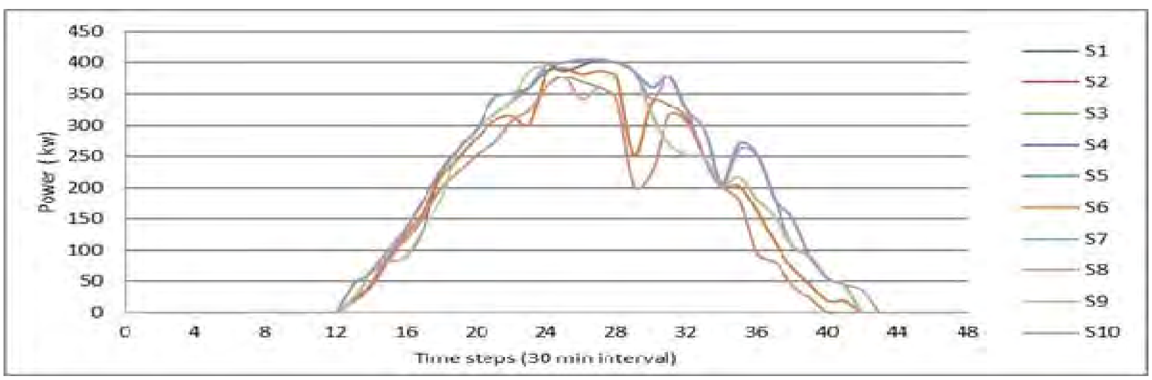

Figure 25. Potential PV power generated from the 10 different weather forecast scenarios

The different optimal operating costs with respect to each of the 10 scenarios with and without energy storage are represented in Table 7. The costs range between $597.63 to $2,007.71 depending on the forecast scenario used.

The average over the 10 scenarios of the contribution of energy storage is $160.92. This direct gain can favor the integration of energy storage in IHEG, however, further analysis is required to confirm this finding. The analysis should account for the construction and maintenance costs of the energy storage technique being considered. In the case of a FOB, where the stability of the grid is crucial for the continuity of operations and the success of missions, the analysis should account for the importance of energy storage to attain an acceptable level of grid stability.

Table 7. Results of optimizing an IHEG over different weather scenarios

	With storage		Without storage	
	Minimum cost ($)	**Time to solve (s)**	**Minimum cost ($)**	**Time to solve (s)**
Scenario 1	1,651.22	6.9	1,809.81	8.8
Scenario 2	2,004.96	7.01	2,129.06	977
Scenario 3	1,840.46	7.2	1,942.74	17.06
Scenario 4	2,007.71	9.02	2,122.75	22.59
Scenario 5	1,820.74	7.4	1,955.31	20.4
Scenario 6	997.01	8.4	1,279.68	16.9
Scenario 7	1,196.74	7.9	1,311.32	7.3
Scenario 8	757.8	6.7	1,051.21	6.5
Scenario 9	1,832.88	7.14	1,970.94	14.6
Scenario 10	597.63	6.7	724.09	6.2

The time needed to solve the optimization problem using GAMS with a relative optimality gap of 1% is short, ranging from 6.2 to 34.5 seconds, except for scenario 2 without storage, which took 17 minutes, 6 seconds to be solved. In general, the solver needs more time when the IHEG does not have energy storage.

Finally, in order to compensate for the forecast error, we optimize over multiple scenarios. This solution will make it more costly to satisfy the load since it includes additional constraints relative to optimizing over a single scenario. However, because all scenarios represent plausible future outcomes, the resulting plan should perform better in reality than a plan resulting from optimization over a single scenario. The results of optimizing over all the 10 scenarios and over 5 scenarios, for example the 5 odd-numbered, and the 5 even-numbered scenarios, are summarized in Table 8. Note that although we only consider operating costs in this table, we will consider satisfaction of demand in Section IV.E.

Table 8. Results of optimizing over multiple weather forecast scenarios simultaneously

	With storage		Without storage	
	Minimum cost ($)	**Time to solve (s)**	**Minimum cost ($)**	**Time to solve (s)**
All scenarios	2,059.85	16.32	2246	29.05
Scen. 1,3,5,7,9	1,943.06	10.4	2,183.4	7.9
Scen. 2,4,6,8,10	2,052.73	14.08	2,200.15	34.5

As expected, the minimum operating cost by optimizing simultaneously over multiple scenarios is at least equal to the most costly forecast scenario. In this case, the solution of optimizing over all the 10 scenarios simultaneously is slightly more expensive than the solution of optimizing over just 5 scenarios. Note that when optimizing simultaneously over multiple scenarios, the storage continues to play a role in reducing the operating cost.

4. Optimizing over the Average of all Weather Forecast Scenarios

Although our problem instances solve very quickly, computation time may be a consideration in more complex instances. For this reason, one might consider aggregating forecast scenarios in some way. One method of aggregation would involve weighing each scenario according to some notion of its accuracy and then optimizing over the weighted average of all the scenarios. This is somewhat similar to optimizing over the standard published (deterministic) forecast. Additionally, because the wind power produced is a nonlinear function of the wind speed, it is reasonable to consider optimizing over the average wind power produced rather than the average wind speed. We now perform computational experiments using both approaches. For simplicity, we weigh the 10 scenarios equally.

a. IHEG with Energy Storage

When optimizing the operating schedule of the IHEG with energy storage over the average of weather forecasts of the 10 scenarios, the minimum operating cost will be $1,514.51. This cost is slightly greater than the average of the operating cost for the 10 scenarios which is $1,469.06.

The suggested optimal schedule is not intuitive. In fact, the EMC has to turn off all the fuel-based generators temporarily during the hours of peak load. The demand will be fully satisfied by the renewable resources and the energy stored in the batteries. The solver chooses to turn off the diesel generator Gen1 during step 23, because the battery was almost full (240kWh/300kWh) by that time and discharging it will allow the grid to store energy again at time step 25 and dispatch the power to compensate the small deficit in the period between time step 28 and 35. According to what we have seen so far, the real advantage of using energy storage, in addition to the gain in cost, is that the smaller gas generator Gen3 was not required with the energy storage. The small deficit in power, which is usually supplied by Gen3, is now provided by the battery. Even with the loss due to storage and with the additional cost of storage, the power produced by the battery is more economical then the power provided by Gen3.

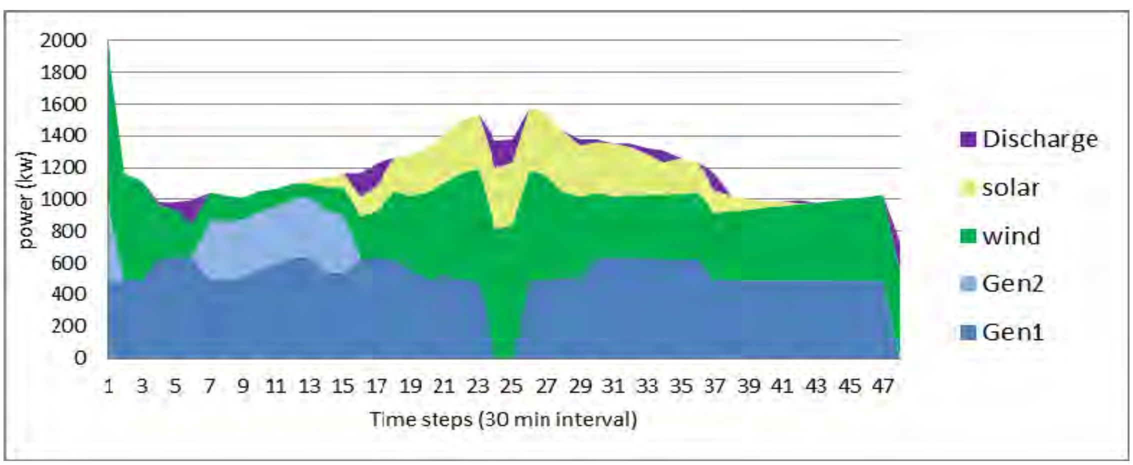

Figure 26. Optimal composition of the power supplied to the IHEG with ES when optimizing over the average of forecast scenarios

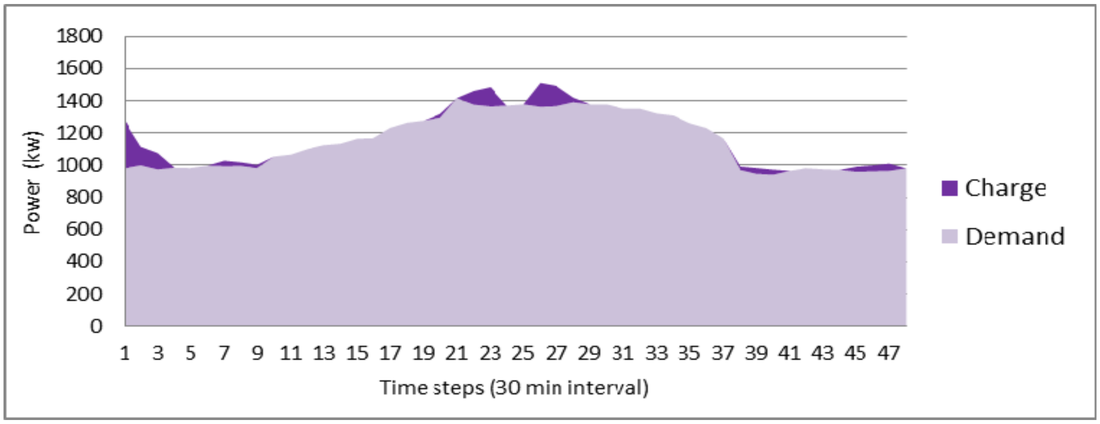

Figure 27. Optimal composition of the load in the IHEG with ES when optimizing over the average of forecast scenarios

b. IHEG without Energy Storage

The elimination of energy storage causes a $121.54 increase in the operating cost. The model attempts to accurately track the power demand by switching from the diesel generator Gen1 to the gas generator Gen2 and then to Gen3.

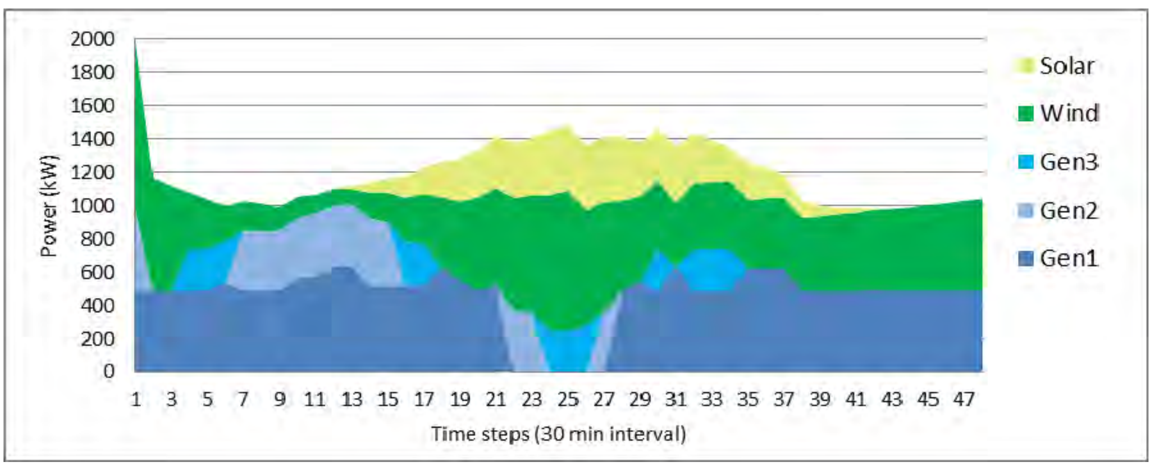

Figure 28. Optimal composition of the power supplied to an IHEG without ES when optimizing over the average of forecast scenarios

5. Optimizing over the Average of Power Output from Different Scenarios

We now consider all 10 scenarios to compute the corresponding potential renewable power productions. Yet, in the optimization, we optimize only over their average.

a. IHEG without Energy Storage

The minimum operating cost of the IHEG with no storage is $1,548.96. The optimal schedule uses all of the three generators, but not simultaneously. When the renewable production is low, the EMC should combine the diesel generator Gen1 with one of the two gas generators. During some periods of the peak load, the whole demand is satisfied by the renewable sources only.

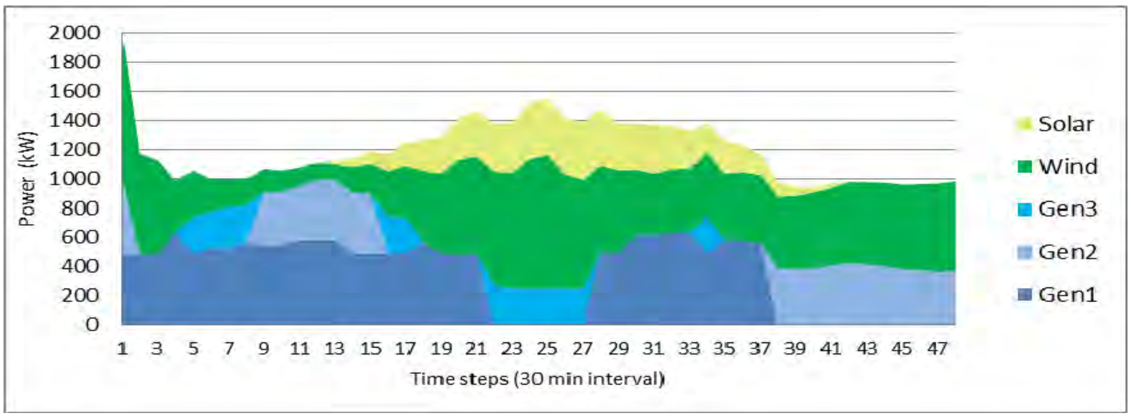

Figure 29. Optimal composition of the power supplied to the IHEG without ES when optimizing over the average of the renewable power output

b. IHEG with Energy Storage

Including energy storage in the model saved $115 from the operating cost. The most impressive observation about this plan is that during some time steps, the peak load was totally supplied without using any fuel-based generator.

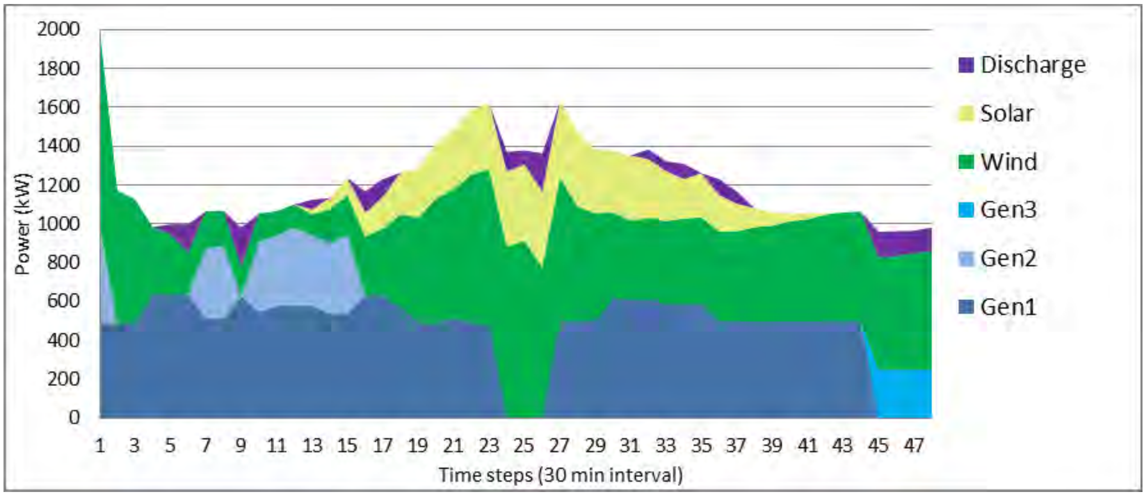

Figure 30. Optimal composition of the power supplied to the IHEG with ES when optimizing over the average of renewable power productions

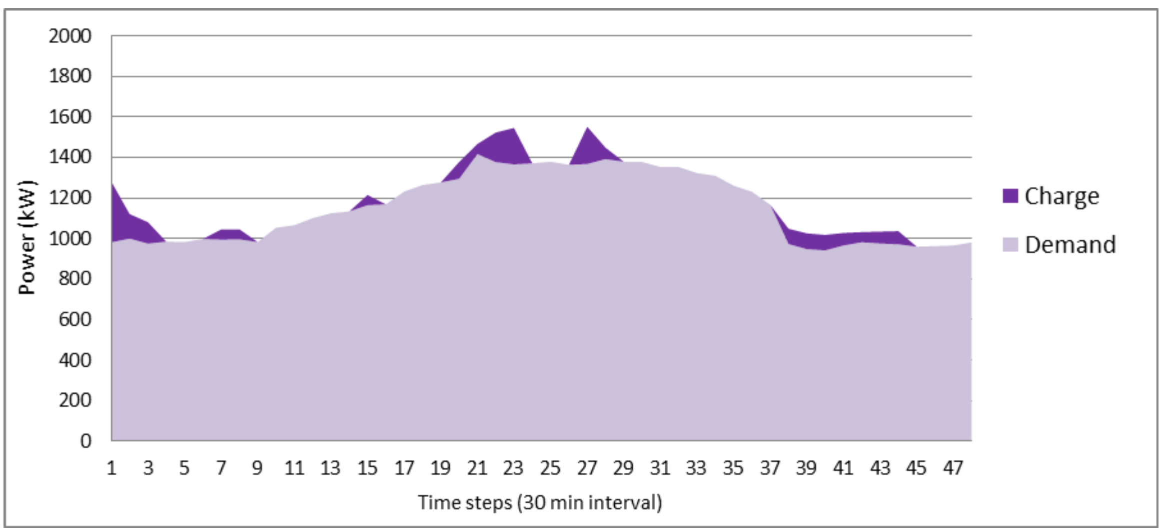

Figure 31. Optimal composition of the load in the IHEG with ES when optimizing over the average of renewable power productions

C. RESULTS OF THE CONNECTED CONFIGURATION OF THE HEG

In this part, we assume that the HEG can be connected to the commercial grid and that it is possible to sell back energy.

1. Analysis of the Optimization over Weather Forecast Scenario S1

The composition of the total supplied energy and the total load that result from solving the optimization problem with respect to weather forecast scenario S1 are presented in Figures 32 and 33, respectively. The optimal operating cost for the configuration with energy storage was $1,599.05.

When both renewable sources and the diesel generator Gen1 become unable to satisfy the demand, the shortage in power is supplied either from the gas generator Gen2 or by the commercial grid when the deficit is less than the minimum possible power production of Gen2.

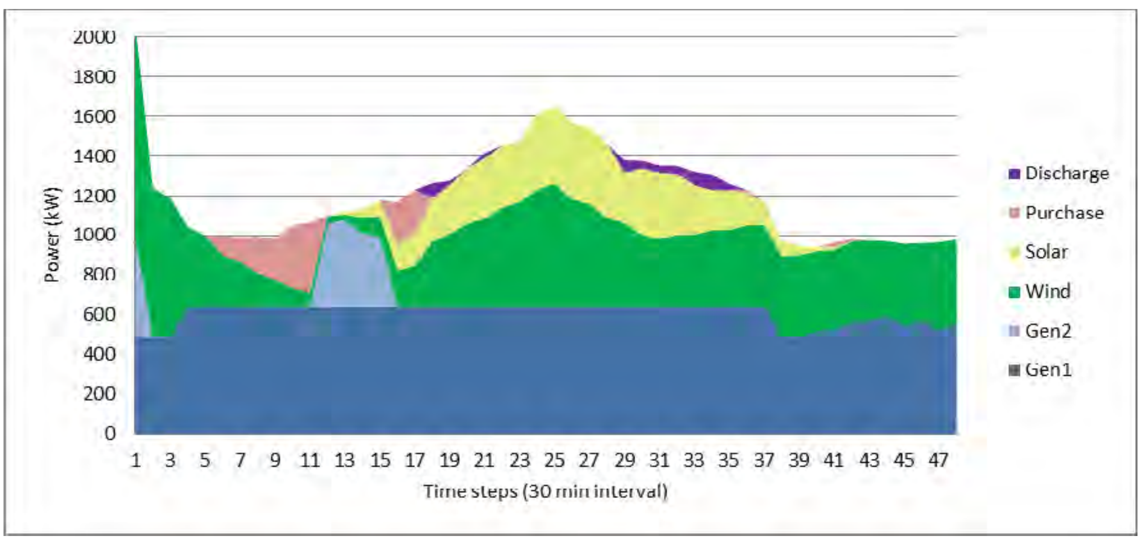

Figure 32. Optimal composition of the power supplied to the HEG with ES when optimizing over weather forecast scenario S1

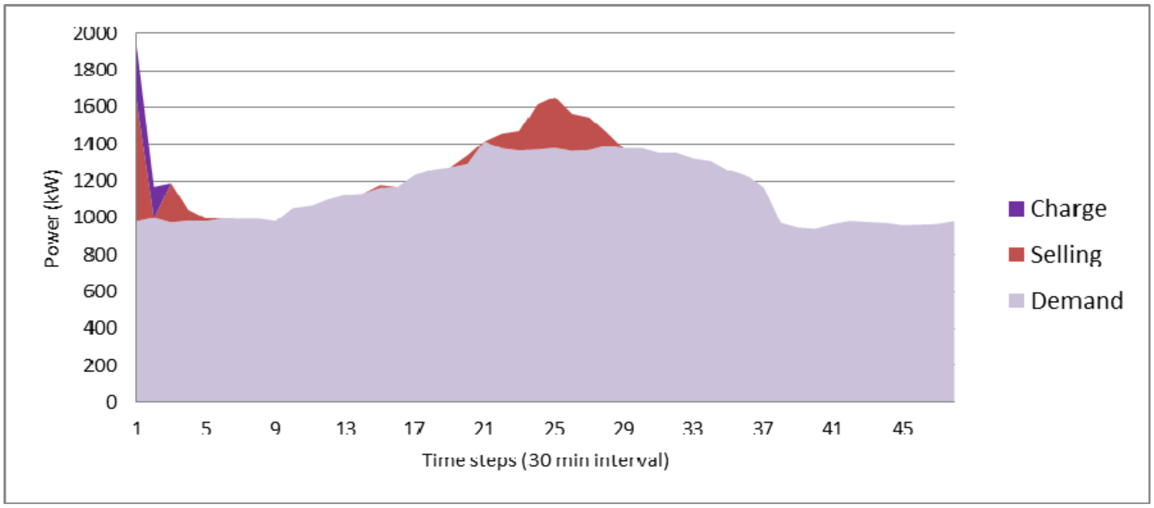

Figure 33. Optimal composition of the total load of the HEG with ES when optimizing over weather forecast scenario S1

Note that during the peak load, the optimal schedule suggests selling back energy to the grid while keeping the diesel generator running at its maximum speed. This can be explained by noting that the selling price of electricity is high at the same time the renewable energy production is at its maximum level. Under these conditions, it becomes profitable to produce energy with the diesel generator to satisfy the load and sell the excess production.

2. Comparison of the Optimizations over Different Scenarios

Similarly to the IHEG configuration, the minimum operating cost varies considerably depending on the weather forecast scenario used (see Table 9). The minimum operating cost ranges between $142.15 and $1,943.87.

Table 9. Results of the connected HEG optimization over different weather scenarios

	With storage		**Without storage**	
	Operating Cost ($)	Solve time (s)	Operating Cost ($)	Solve time (s)
Scenario 1	1,599.05	6.4	1,602.62	6.8
Scenario 2	1,943.87	7.1	1,947.29	6.8
Scenario 3	1,790.28	6.4	1,803.97	7.4
Scenario 4	1,952.95	6.4	1,952.95	7.2
Scenario 5	1,762.72	6.2	1,782.84	6.2
Scenario 6	901.66	6.9	901.76	7.2
Scenario 7	1,027.89	6.8	1,027.89	6.7
Scenario 8	582.13	6.4	582.63	6.6
Scenario 9	1,782.47	7.5	1,783.49	7.1
Scenario 10	142.15	6.6	142.15	6.63

The main takeaway from this analysis is the degradation of the contribution of the energy storage: unlike the isolated configuration, the energy storage did not help to reduce significantly the total operating cost. The 2 ₵/kwh storage cost in addition to the 20% loss factor of storage made storing power generated from the fuel generator less profitable in the presence of a commercial grid to which we can sell the leftover production or from which we can buy the power needed.

The solving process for all of the 10 scenarios separately takes a short time to find an optimal schedule. The average solve time was 6.67 seconds.

3. Optimization over Multiple Scenarios Simultaneously

Table 10 presents the results from optimizing over multiple weather forecast scenarios. The minimum operating cost becomes less variable and tends toward the cost of the most restrictive plan, which optimizes over all the 10 scenarios. The influence of the storage is still insignificant and the solve time is still short.

Table 10. Results of the optimization of a connected HEG over different subsets of weather forecast scenarios

	With storage		**Without storage**	
	Operating cost ($)	Time to solve (s)	Operating cost ($)	Time to solve (s)
Scen. 1,2,3	1,939.07	9.4	1,995.46	6.9
Scen. 8,9,10	1,780.52	8.8	1,783.49	7.4
Scen. 4,5,6,7	1,939.24	8.6	1,953.31	6.7
All Scenarios	1,990.39	14.5	2,089.8	7.4

4. Optimization of a Connected HEG over the Average of Weather Forecasts

The cost of optimizing the connected HEG over the average of weather forecasts is $1,428.59 with energy storage and $1,429.59 without. The operating plan is very similar to the optimal plan of the optimization over scenario S1.

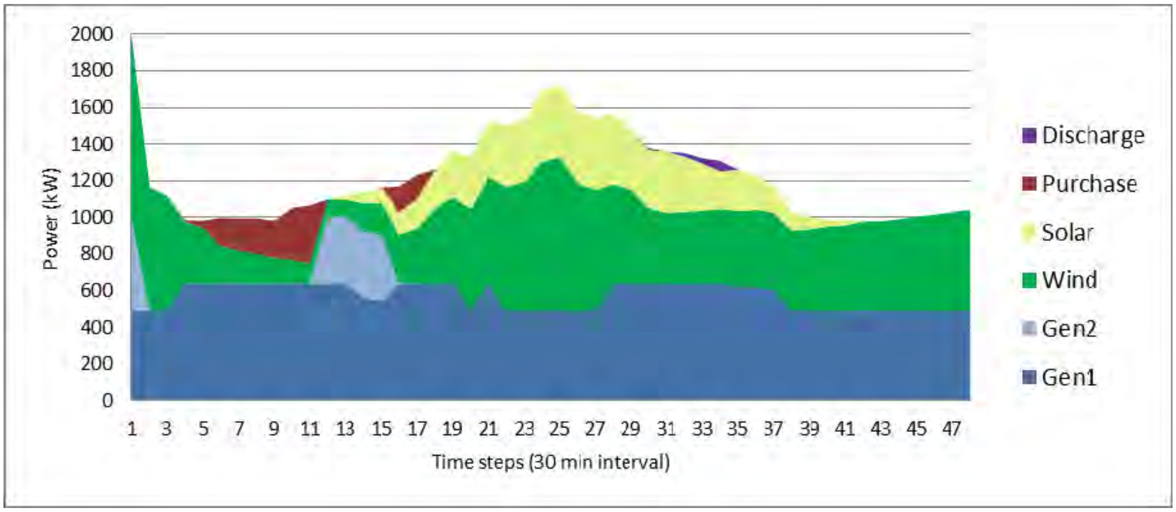

Figure 34. Optimal composition of the power supplied to the HEG with ES when optimizing over the average weather forecasts

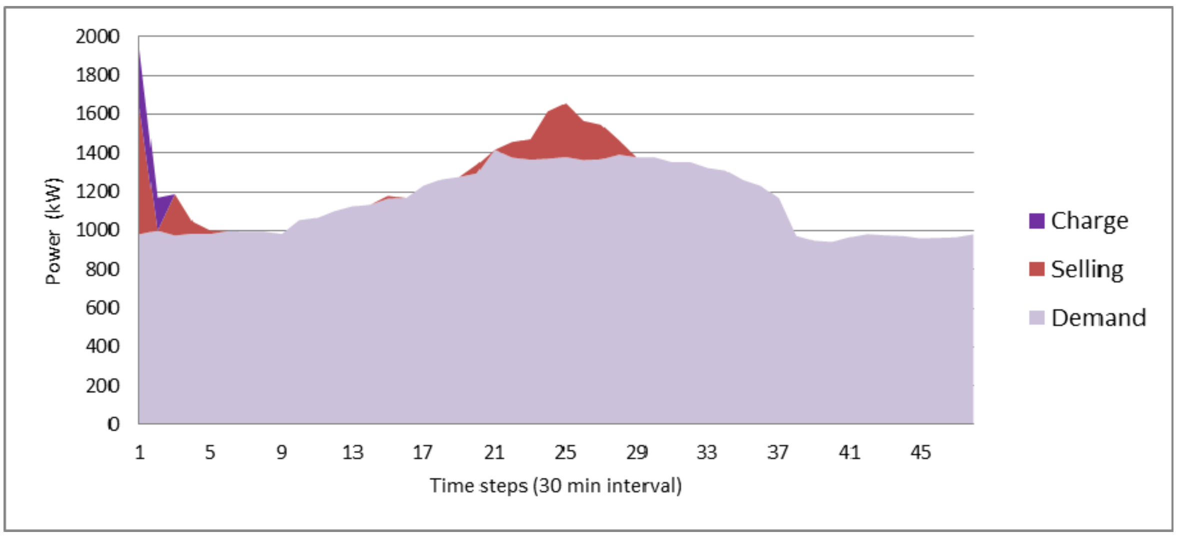

Figure 35. Optimal composition of the total load of the HEG with ES when optimizing over the average weather forecasts

5. Optimization of a Connected HEG over the Average Renewable Power Production

The minimum cost found after optimizing the connected HEG over the average of the renewable power production is $1,326.48 and it is 23% cheaper than when optimizing over the average weather forecasts. The integration of energy storage to the model did not have any influence on the cost or the operating plan.

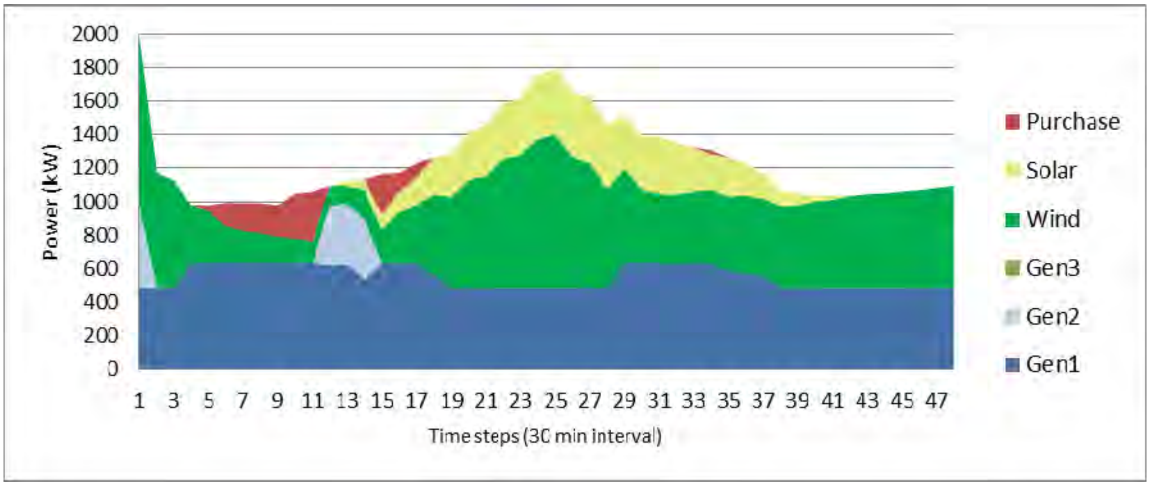

Figure 36. Optimal composition of the power supplied to the HEG with ES when optimizing over the average of the renewable energy productions

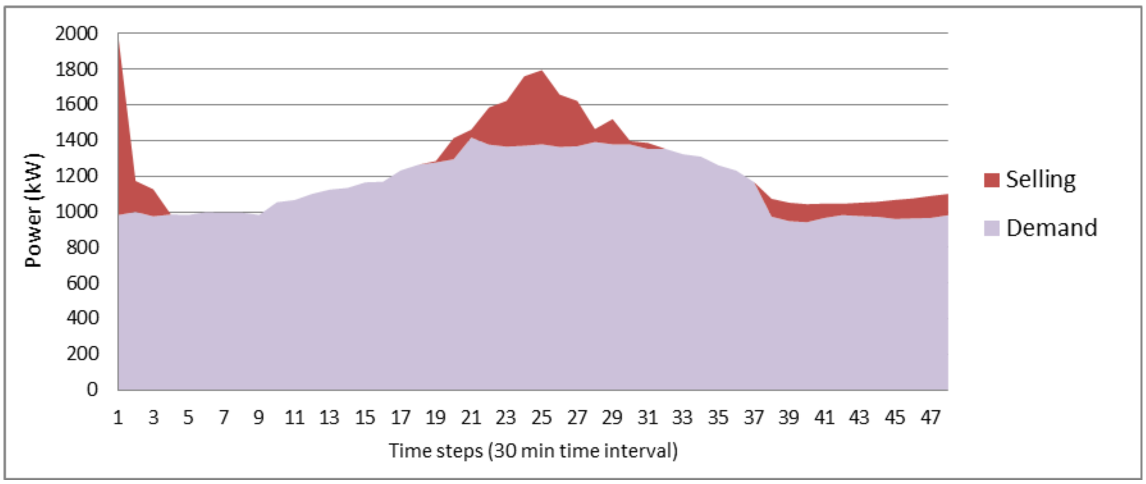

Figure 37. Optimal composition of the total load of the HEG with ES when optimizing over the average of the renewable energy productions

D. RESULTS SUMMARY

We now provide a summary of the total operating cost for both isolated and connected mode that result from various optimizations.

1. Comparison of the Wind Power Productions

Since the wind power is not strictly proportional to the wind speed, the average of wind power productions from the forecast scenarios is different from the wind power generated from the average of the wind forecasts. Figure 38 presents a comparison of the different wind power generated from different scenarios, from the average of forecast scenarios in addition to the average power over all scenarios.

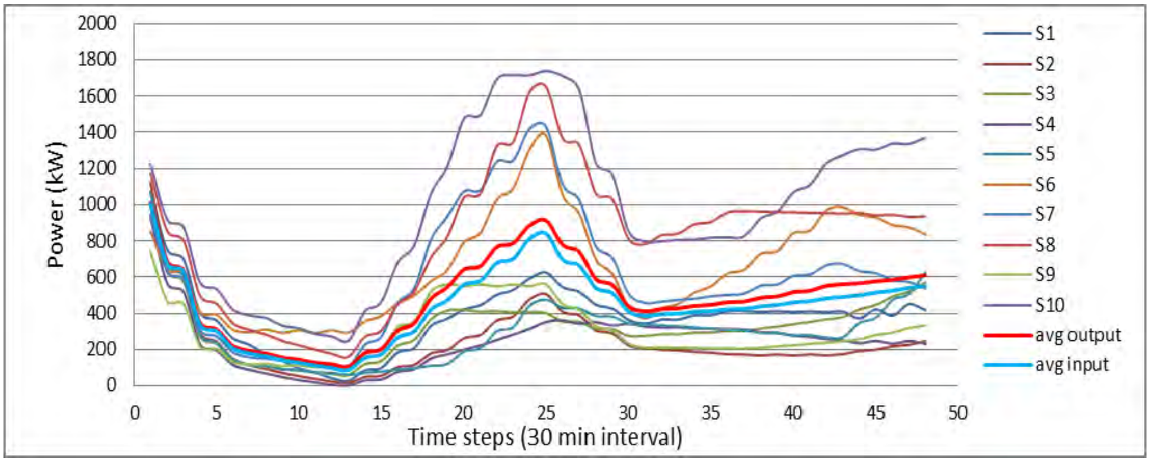

Figure 38. Wind power by scenario forecast vs. the wind power generated by the average wind over all scenarios (avg input) and the average wind power from all the scenarios (avg output)

2. Results of the IHEG Optimization

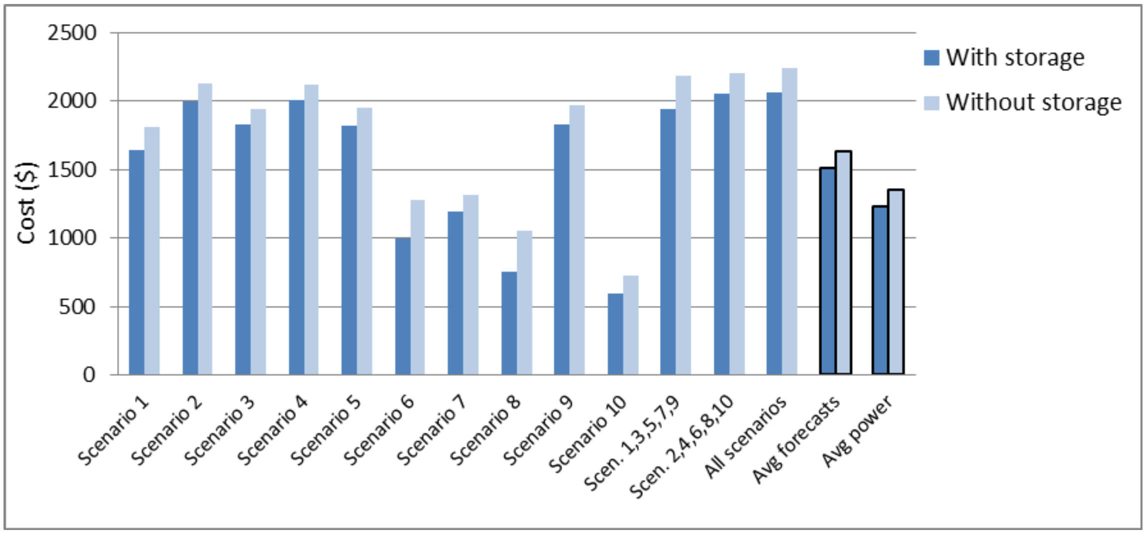

Figure 39. Minimum operating costs when optimizing the IHEG

3. Results of the Connected HEG Optimization

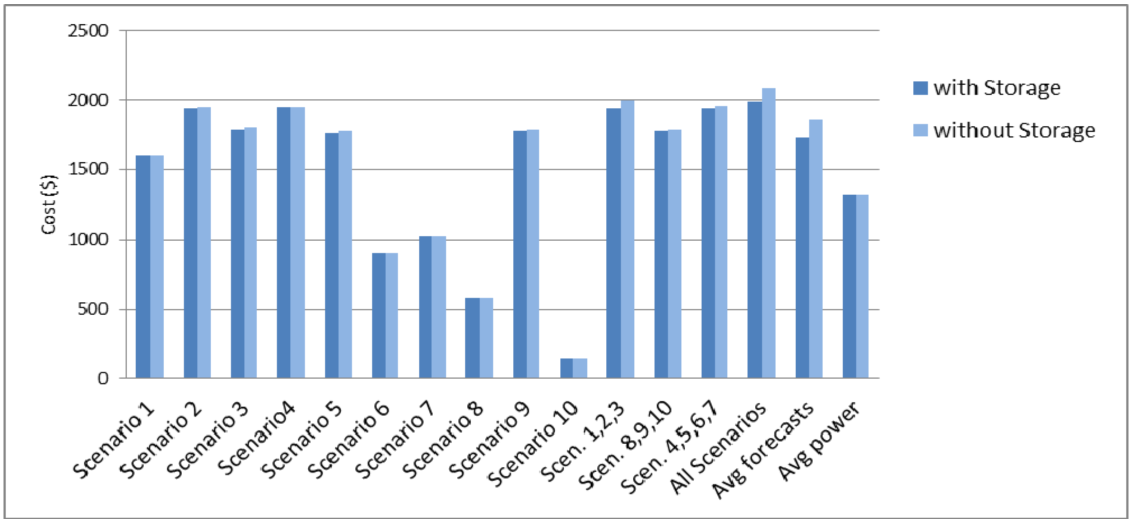

Figure 40. Minimum operating costs when optimizing the connected HEG

E. TEST OF THE OPERATING PLANS

It is unsafe to focus on operating cost as the only criterion when the EMC wants to decide which optimal plan to adopt. The optimization that leads to the cheapest cost had probably used a very optimistic and usually less probable data. In addition to the cost, we need to check which of the optimizations provide the most robust plan.

To check the effectiveness of the optimal schedule suggested by the optimization model, we need, first of all, to find the real weather parameters observed at the location of interest and during the same time window of the plan. Then, we have to use the weather data to evaluate the real renewable power generated. After that, we can add the renewable power production to the fuel-based power generated when the optimal schedule is executed. The robustness of the plan is defined by how well the real total production, when the plan is executed, meets the demand.

1. Detailed Test with Scenario S1

Airports maintain detailed histories of wind observations; however, this data is inappropriate for our analysis. Wind observations are typically taken at ground level and are not representative of conditions at higher altitudes, such as the 80m level at most wind turbines operate and which our forecast data occurred. Thus, we assume that our weather scenarios represent all possible future outcomes; in other words, the actual wind speed may correspond to any of the scenarios S1-S10. In this section, we focus on the case in which scenario S1 actually occurs.

To check the quality of various operating schedules generated from the different optimizations, we sum:

- the renewable power production generated by the weather conditions forecasted by scenario S1,
- the fuel-based generation while executing the operating schedule from the optimization
- the power generated from the energy storage facility according to the operating schedule.

This sum is defined as the total power supply to the grid. The accuracy of a plan is defined by how close the total power supply matches the total demand without going below it. The total power demand is simply the sum of the regular power consumption that we defined and the power needed to charge the battery according to the operating schedule.

When we optimize an IHEG without energy storage over scenario S2 and scenario S1 occurs, the optimal plan is able to meet the demand during the majority of the time window. We see two shortfall periods around 2:30 p.m. and around 6:30 p.m. (see Figure 41).

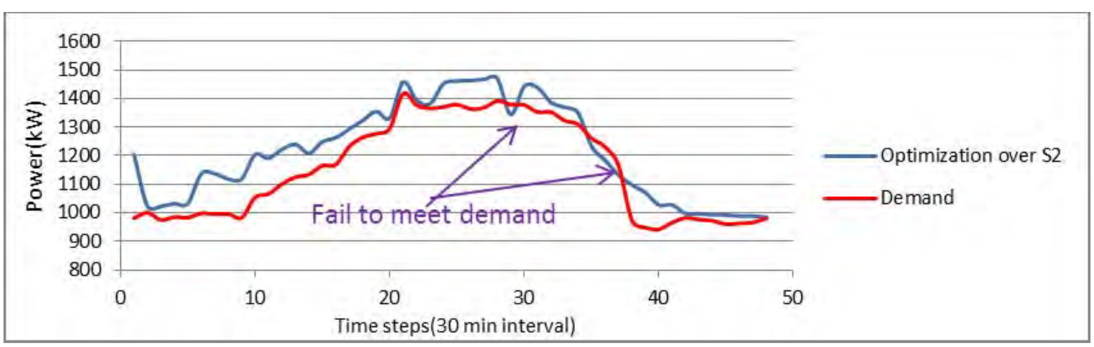

Figure 41. Power supply from optimization of an IHEG without energy storage over scenario S2

When we optimize an IHEG without energy storage over scenario S3 and scenario S1 occurs, the optimal plan fails by small quantity to meet demand at 1:00 a.m. for about one hour period, but it is successful for the rest of the time horizon (see Figure 42).

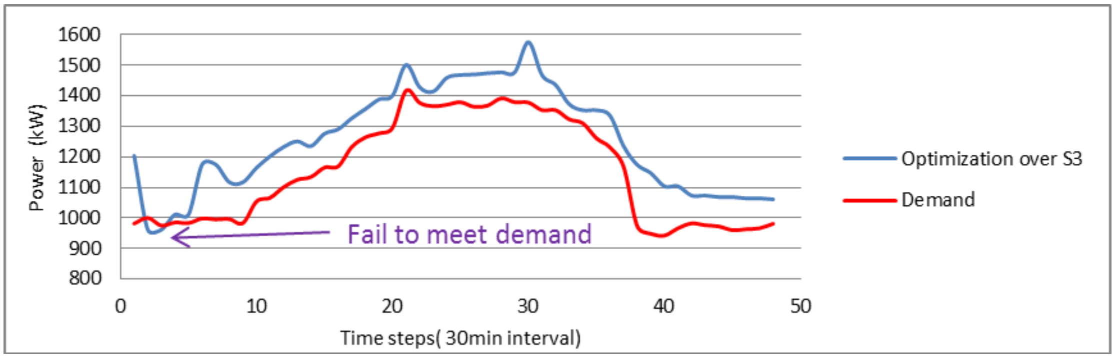

Figure 42. Power supply from optimization of an IHEG without energy storage over scenario S3

When we test the plan from the optimization of an IHEG without energy storage over scenario S10 and scenario S1 occurs, the power supplied is very close to the demand. Yet, this plan fails many times to meet the demand. However, the shortfalls are very small.

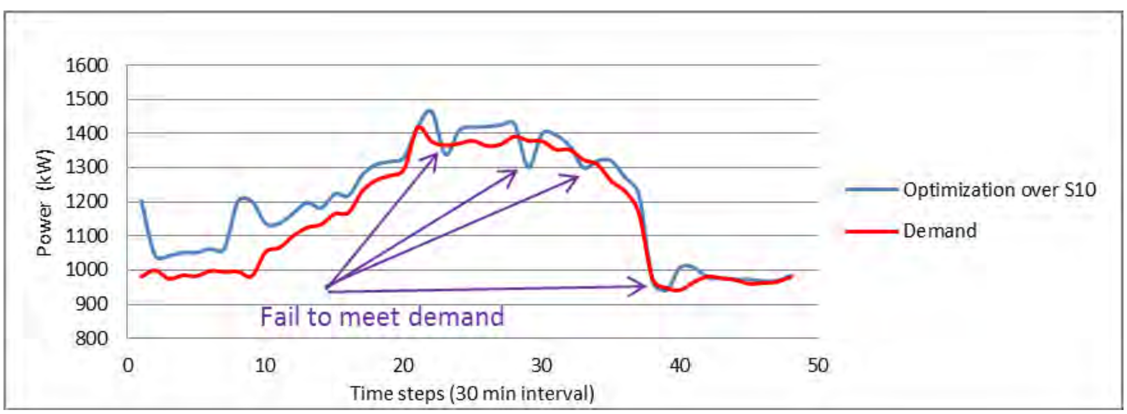

Figure 43. Power supply from optimization of an IHEG without energy storage over scenario S10

Optimizing the IHEG without energy storage over a subset of scenarios (S2, S4, S6, S8, and S10) did not help to eliminate the shortfall seen with the S2 optimization plan as shown in Figure 44.

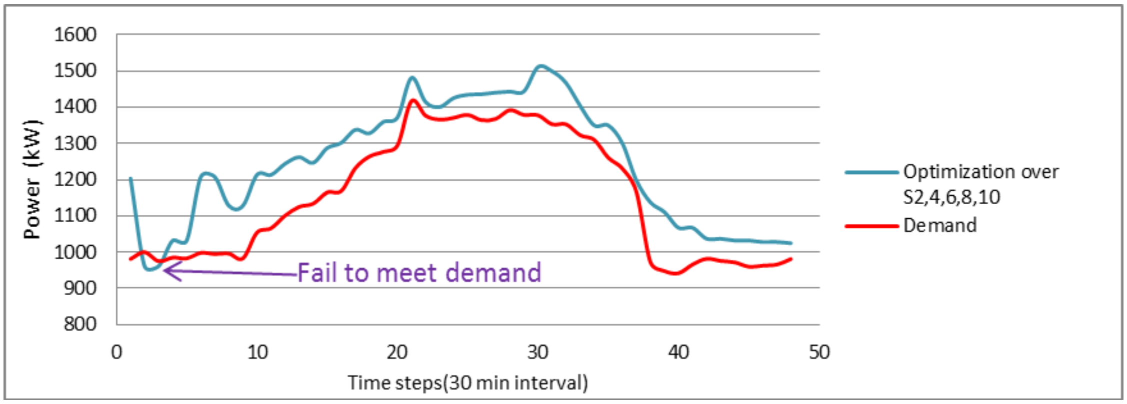

Figure 44. Power supply from optimization of an IHEG without energy storage over scenarios S2, S4, S6, S8, and S10 simultaneously

Expanding the subset of the scenarios used in the optimization make it more costly to meet the demand reflected in the increased gap between the total supply curve and the total demand curve. Yet, the shortfall in the first few hours of model run still persists.

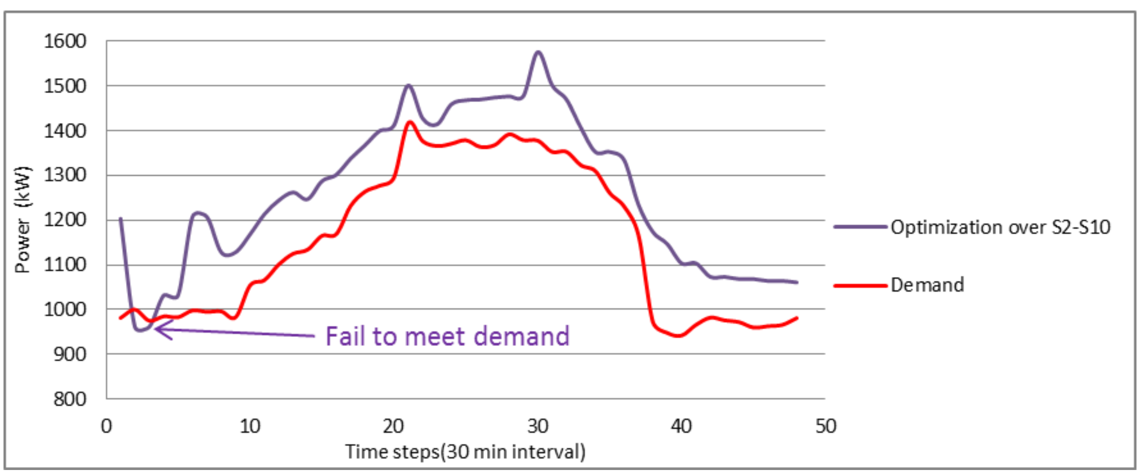

Figure 45. Power supply from optimization of an IHEG without energy storage over scenarios S2 through S10 simultaneously

We discussed earlier in this chapter the possibility of optimizing over the average weather forecasts and over the average renewable power output. The plan from the former optimization method was successful to meet demand at all the time steps. However there is a considerable gap between the total power produced and the power needed that raises the operating cost. The latter type of optimization that uses the average of renewable power productions provided a total supply very close to the total demand even though it fails, by small amounts, to meet the demand in some time steps. The results given by the optimization over the average renewable power production are very interesting and insightful. We suggest further analysis before recommending it for grids that allow temporary small shortfalls in power supply. The same is true for the optimization over the average renewable power production: after further analysis, this efficient optimization model could be recommended to be considered for grids that are very sensitive to shortfalls in power supply.

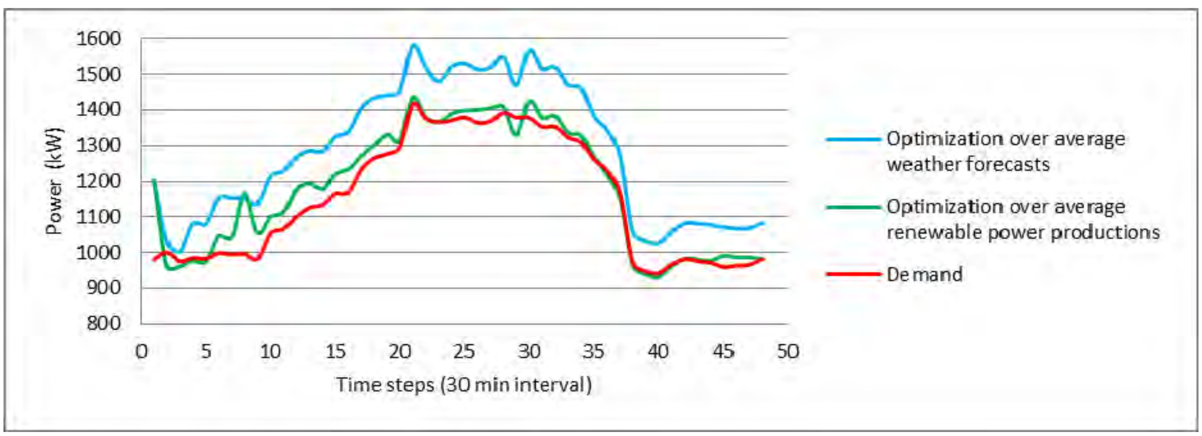

Figure 46. Power supply from the optimization of an IHEG without energy storage over the average of wind forecast scenarios and over the average of renewable energy productions

2. Summary of Tests over Different Scenarios

Table 11 presents the total excess and shortage of energy production when we optimize over the different scenarios in the first column and we consider that scenarios in the rows happen. We represent both shortage and excess of production, because we assume that the excess of power production in one time step cannot cancel out or reduce the shortage in another step.

Table 11. Total excess and shortage of energy production in kWh when one of the scenarios happens

Scen. optimizied over \ Scen. that happened		S1	S2	S3	S4	S5	S6	S7	S8	S9	S10
S1	Excess	203	263	102	219	693	131	1,152	130	901	513
	Shortage	0	798	1326	849	84	851	0	631	62	371
S2	Excess	1,105	227	175	342	1,371	305	1,914	604	1,655	904
	Shortage	140	0	637	211	1	263	0	342	54	0
S3	Excess	1,726	996	272	906	2105	785	2648	996	2,337	1,639
	Shortage	26	35	0	40	0	8	0	0	1	0
S4	Excess	1,202	422	186	263	1,506	361	2,045	657	1,733	1,036
	Shortage	106	64	517	0	4	188	0	265	0	0
S5	Excess	246	105	69	121	303	110	890	112	669	298
	Shortage	349	946	1,598	1,057	0	1,135	43	918	136	462
S6	Excess	1,189	516	117	427	1,571	240	2,111	566	1,809	1,102
	Shortage	26	92	382	98	3	0	0	107	10	0
S7	Excess	32	15	3	13	152	4	295	10	251	115
	Shortage	685	1,407	2,084	1,500	400	1,580	0	1,367	269	830
S8	Excess	998	578	81	488	1,392	317	1,915	263	1,628	937
	Shortage	32	351	542	356	20	273	0	0	26	32
S9	Excess	161	120	68	73	365	109	678	99	357	307
	Shortage	440	1,138	1775	1,186	239	1,311	9	1,082	0	648
S10	Excess	570	74	51	75	815	79	1,319	181	1,072	275
	Shortage	234	477	1,143	573	73	666	35	549	100	0
Average wind	Excess	3,090	2,352	1,667	2,256	3,496	2,168	2,168	4,039	2,387	3,726
	Shortage	0	0	4	0	0	0	0	0	0	0
Average Power	Excess	635	200	104	168	969	139	1,498	199	1,218	549
	Shortage	86	389	982	453	14	512	0	354	32	61

The excess in power production in the first time step was very important for all the plans because of the initial conditions about fuel-based generators that we set. We chose to not consider the excess of power production of the first time step and to not include it in the total. Also, note that we will not have shortage when we assume that the scenario that we are optimizing over actually happens, but we still have some excess of production and that is because of the fact that the fuel-based generators cannot generate small power output.

We can see from the optimization plans studied that the safest plan is provided by optimizing over the average wind forecasts. However, this plan is very costly and we have too much excess of power production.

Ideally, one would run computational experiments over many forecast datasets in order to identify consistent trends in behavior. Due to time constraints we were unable to do this. However, future research may extend our work by running additional computational experiments.

F. ROLLING HORIZON

The focus of this thesis is to help an EMC find the optimal operating schedule not just over a limited time window but over long and continuous horizons. Unfortunately, weather predictions over long time horizons are highly uncertain. For this reason, we recommend solving the problem with time cascades; in other words, solve over a time window shorter than the problem horizon and advance the window for each successive solve. Additionally, overlapping the time windows helps to avoid end-of-horizon effects. The operating plan should be fixed before each window. In the following example the cascade window is 24 hours (48 time steps) and the advance is 12 hours.

The goal of this part is to provide a concrete example of how the optimal schedule can change when we solve it with time cascades. The weather data used in this part comes from the same WRF weather forecasts data for the two locations cited before. The first set of forecasts started December 2, 2008 at midnight, while the updated forecast was available at the same day at noon. We will check how the optimal schedule for the second half of the day and the cost will change when we use time cascades with the updated weather forecasts.

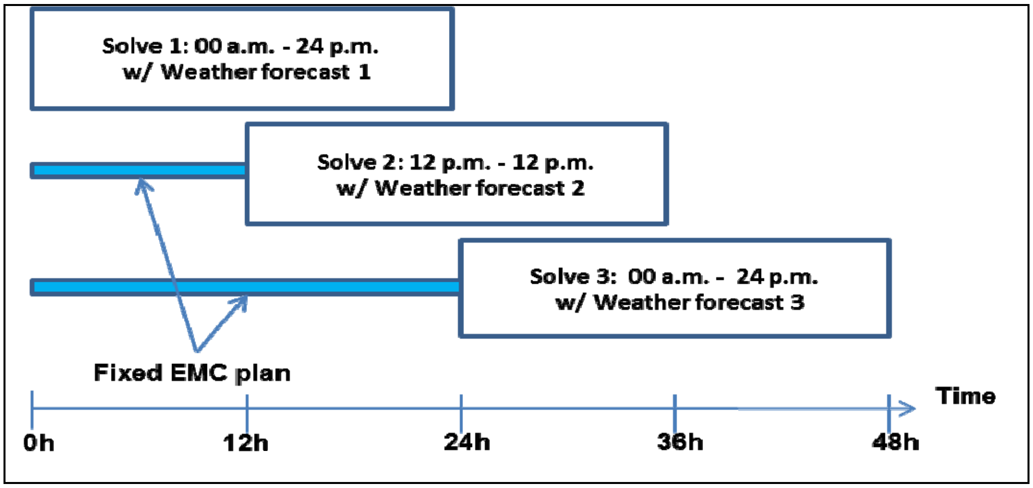

Figure 47. Schematic representation of optimization with time cascades

1. IHEG without Energy Storage

Figures 42, 43, and 44 represent respectively the initial, the first and the second set of updated wind forecasts. The initial weather forecast covers 24 hours starting from December 2, 2008 at midnight, while the first set of updated forecasts covers 24 hours starting from December 2, 2008 at noon. The second set of updated forecasts covers also 24 hours, starting from December 3, 2008 at midnight.

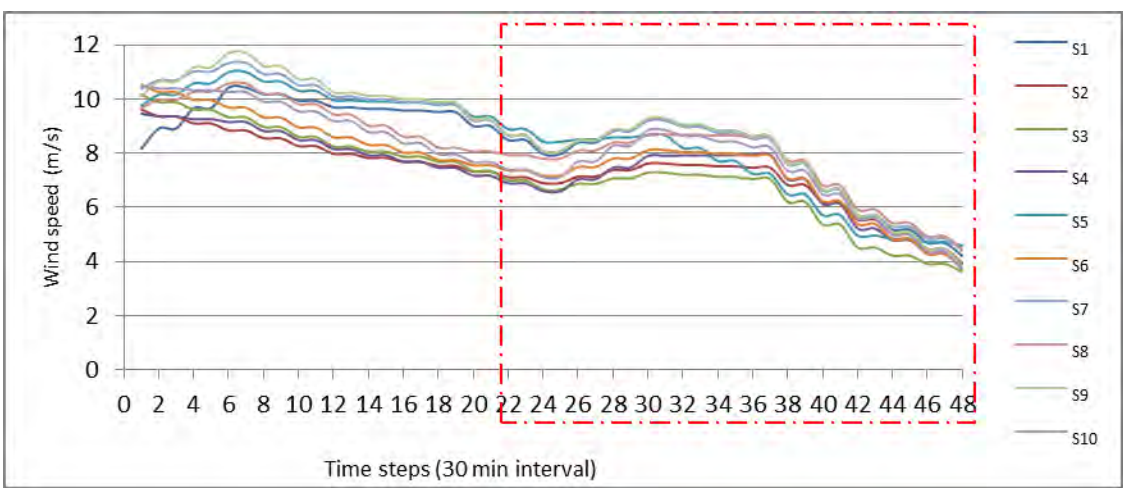

Figure 48. Initial set of wind forecasts at location A

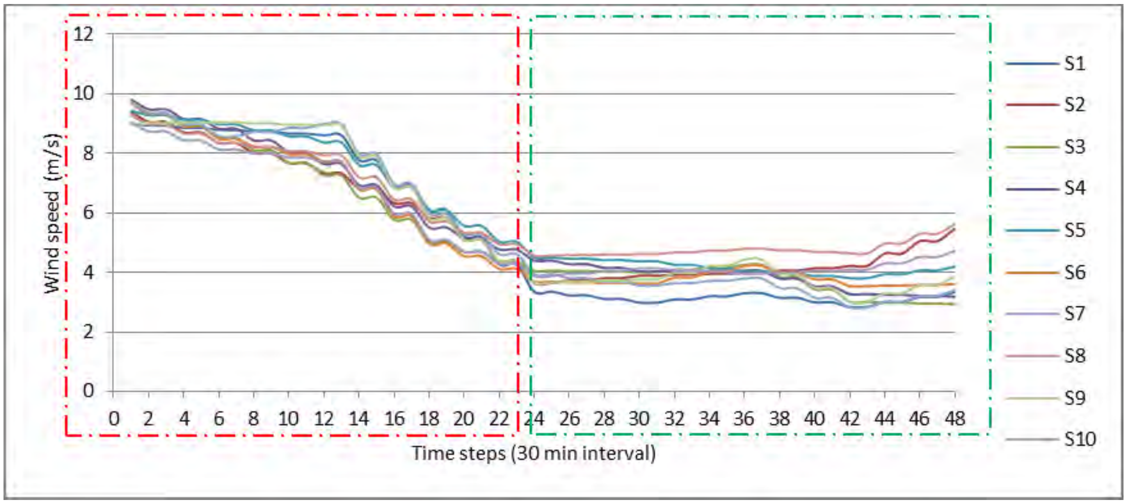

Figure 49. First set of updated set of wind forecasts at location A from December 2, 2008, at midnight to December 3, 2008, at midnight

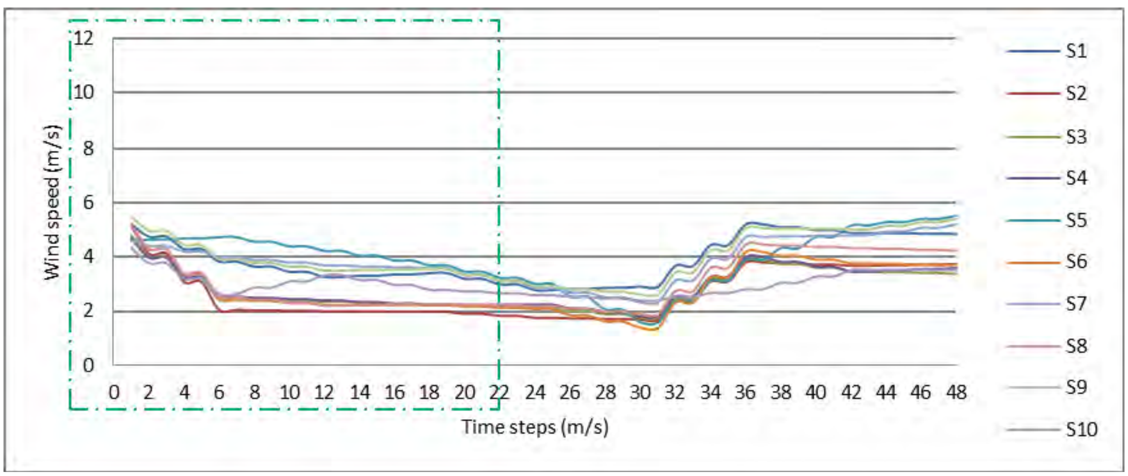

Figure 50. Second set of updated wind forecasts at location A from December 2, 2008, at midnight to December 3, 2008, at midnight

The wind forecasted by the first set of updated forecasts is slightly different from the original forecasts. For instance, the wind predicted on December 2 between noon and 02:00 p.m. by the updated forecast is higher than by the initial forecast set. This difference between the two predictions is reflected in the total operating cost and in the operating schedule.

In fact, when just the initial set of forecasts is used, the minimum cost when optimizing over all scenarios is $2,308.36 and the initial operating schedule consists only of using the diesel generator Gen1 and the gas generator Gen2. When we consider the first set of updated forecasts, the operating cost of the same time period becomes $2,195.75. The operating schedule changes as well; in some time periods, the smaller gas generator Gen3 is used in lieu of Gen2.

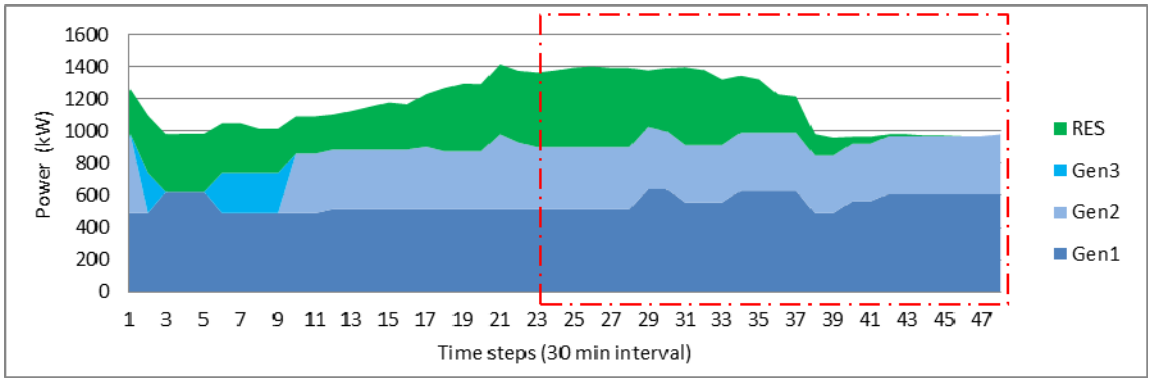

Figure 51. Optimal composition of the power supplied to the IHEG without energy storage when just the initial set of weather forecasts is considered

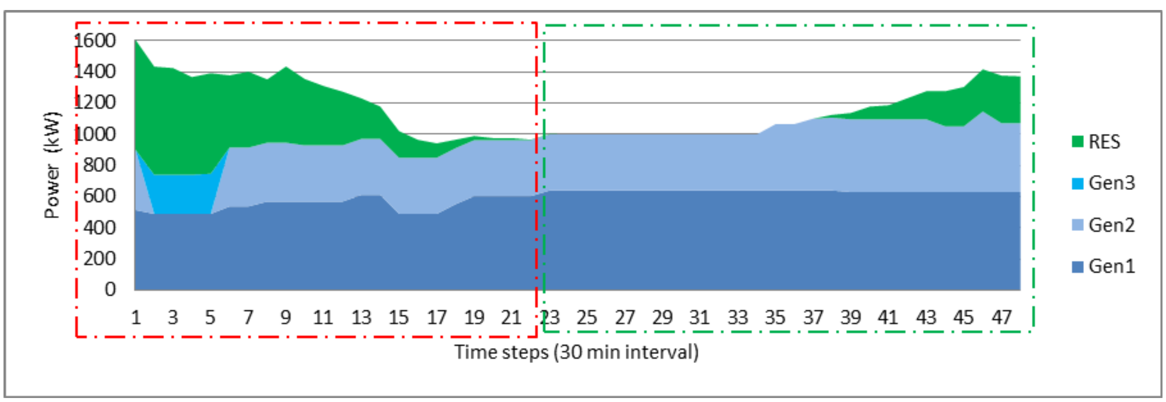

Figure 52. Optimal composition of the power supplied to the IHEG without energy storage when the first set of updated weather forecasts is considered

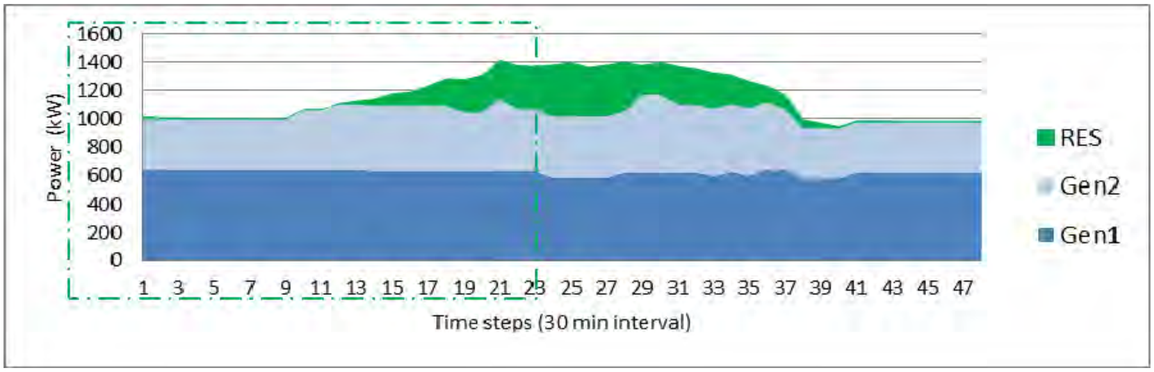

Figure 53. Optimal composition of the power supplied to the IHEG without energy storage when the second set of updated weather forecasts is considered

The optimal plan does not change considerably after including the second set of updates because the wind speed forecasted by both sets of updates is very low; in fact, it is less than the cut-in speed of the wind turbines.

2. IHEG with Energy Storage

We noticed earlier that when optimizing an IHEG that includes energy storage, the optimal schedule will use up all the energy stored during the run and will not account for the future demand. This end-of-horizon effect can happen when optimizing over a limited time horizon. However, the rolling horizon approach can mitigate this effect and also help to reduce the effect of the initial conditions.

The initial optimal plan for this configuration without weather forecast updates costs $2,205.16, and it does not involve the gas generator Gen3. When optimizing the operating plan using the new weather forecasts, the cost becomes $1,778.37, and the gas generator Gen3 is now used.

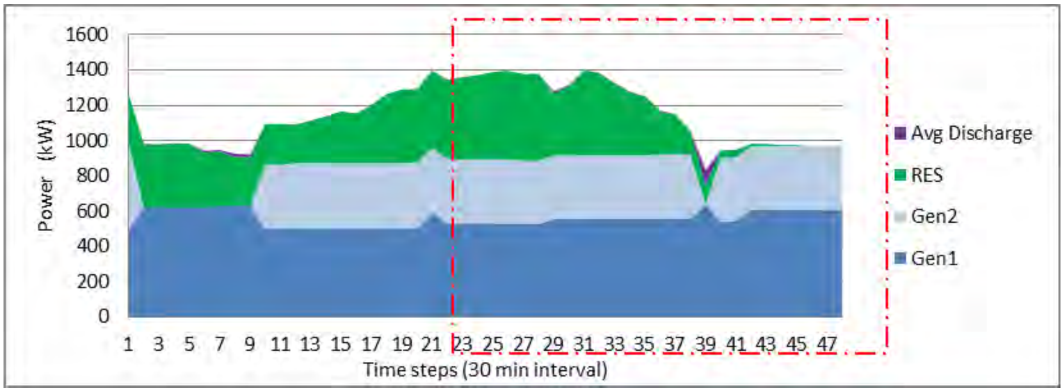

Figure 54. Optimal composition of the power supplied to the IHEG without energy storage when just the initial set of weather forecasts is considered

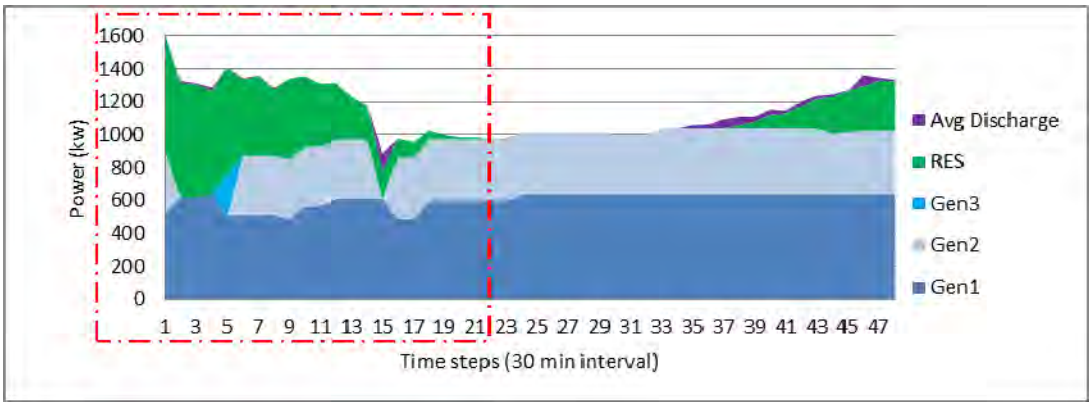

Figure 55. Optimal composition of the power supplied to the IHEG with energy storage when the first set of updated weather forecasts is considered

In this particular example, the operating cost is reduced after using the updated wind forecast because, as mentioned before, the second set of weather forecast predicts stronger wind than what it was predicted by the initial forecasts. Nonetheless, the main goal from the use of the rolling horizon technique is not to reduce the operating cost but to provide a more robust plan based on more accurate weather forecasts and to reduce the end of horizon effect. For example, when optimizing over just the first day, the battery was totally empty at the end of the time horizon. But, when we expand the optimization to include the first half of the second day, the battery contains 160 kWh (53% charge) at the end of the first day. The rolling horizon approach can be applied with the connected HEG in the same way and for the same reasons discussed in the IHEG analysis.

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V. CONCLUSIONS AND FUTURE WORK

A. CONCLUSIONS

The integration of renewable energy sources in microgrids is now a cheap and promising alternative. Yet, it is hampered by the intermittency of the renewable power production. The goal of the thesis is to help the energy management center of an HEG to establish a robust and cost efficient operating plan. One of the strengths of the model established is its flexibility. The same model can be easily altered to include or eliminate a particular component like energy storage or to define the configuration of the grid modeled. This flexibility permits us to conduct diverse analyses and to explore how the optimal operating schedule and the minimum operating cost are affected by the presence or absence of a particular component or capability.

In the analysis part of the thesis, we considered two different configurations of the HEG based on whether or not it is connected to the commercial electric grid. We analyzed each configuration with and without energy storage. In order to mitigate the uncertainty caused by the error in weather forecasts, we considered 10 different scenarios of weather forecasts. The results of the optimization with respect to a single weather scenario were very different in terms of their optimal costs and optimal schedules. For instance, the minimum operating cost from optimizing the connected HEG without energy storage over the 10 different scenarios separately ranges between \$142.15 and \$1,952.95 for the same initial condition, the same power demand, and over the same time horizon. In order to come up with a robust plan, we tested different approaches such as optimizing over all the scenarios or some subsets of them, optimizing over the average of weather forecasts, and optimizing over the average of renewable power productions.

Based on the model assumptions and characteristics and the power demand used, we found that the integration of energy storage is more beneficial in the isolated configuration of the HEG. The gain from including energy storage was around 10% of the total operating cost regardless of the weather forecast. However, the energy storage capability did not have any significant economic advantage when included in the connected HEG. It was more profitable to EMC to compensate the small shortfalls in power from the commercial grid than from energy stored in the battery.

In the last part of the analysis, we focused on how the cost and the optimal plan would change when we run it over longer period with updates of weather forecast every 12 hours. The rolling horizon method was used to minimize of the effect of the initial conditions, to minimize the end-of-horizon effect, and to provide a more robust plan using more accurate weather forecasts. Our study found that there were considerable differences in the optimal cost and plan depending on whether or not we include new weather updates.

B. FUTURE WORK

We suggest running the model for a few weeks using the rolling horizon technique in order to reach more consistent and robust conclusions, especially about the role of energy storage. It is better to use more frequent weather updates, especially given that this is within the capabilities of the WRF model.

In the second part of the analysis that seeks to evaluate the quality of the suggested plan, we compared the power supplied that we will have after applying the optimization plan with the real observed weather conditions and the total power demand. Because of time limitations, we could not get the historic weather data but instead we used the weather forecasts from our scenarios in place of the observed data. The plan from the optimization over the average of wind forecasts was able to meet the demand at all the time steps. Nonetheless the other plans met very closely the power demand for a big portion of time and failed in few time steps with very small shortfalls. The plan from the optimization over the average renewable power productions was interesting in that the total power supplied was very close to the total demand, even though this plan fails to meet the demand in 8 time steps, but with power shortfalls less than 50 kW and a total deficit of energy of around 35 kWh. However, before solid conclusions can be reached, we recommend running similar computational experiments using additional weather forecast data. Moreover, we recommend evaluating the plan resulting from optimization over all scenarios simultaneously, as this plan is guaranteed to be the most robust of the plans we considered.

From the analysis of results done in Chapter IV, we noticed that some plans were cost efficient, but they failed to meet the demand in some time steps. An interesting variation to our model would be to allow it to fail to meet the demand for a limited number of time steps and with a tolerable amount of power shortfall. We now suggest a candidate formulation that accomplishes this.

We need to define 2 sets of binary decision variables:

- $FAIL_{s,k}$: equals 1 if the model fails to meet demand at time step k for weather scenario s an 0 otherwise.
- $FAILSCEN_s$: equals 1 if scenario s fails to meet demand at any time step k and 0 otherwise.

Also, we define three scalars:

- M : the maximum tolerable power shortfall
- $nFails$: maximum tolerable number of failures to meet demand for all scenarios and all time steps
- $nScenFails$: maximum tolerable number of failures to meet demand during all time steps for each individual scenario.

$$\sum_g PCONTRIB_{g,k} + \sum_w WindP_{w,k,s} + \sum_b PDCHARGE_{b,k,s} + SolarPower_{k,s} + PBUY_k$$

$$\geq PSELL_k + Demand_k(1 - FAIL_{s,k}) + \sum_b \frac{PCHARGE_{b,k,s}}{1-\alpha_b} \qquad \forall\ g \in G,\ k \in K \text{ and } s \in S \tag{Eq. 38}$$

$$\sum_{s,k} FAIL_{s,k} \leq nFails \tag{Eq. 39}$$

$$FAIL_{s,k} \leq FAILSCEN_s \qquad \forall s \in S, k \in K \tag{Eq. 40}$$

$$\sum_s FAILSCEN_s \leq nScenFails \tag{Eq. 41}$$

- Equation 38 is derived from the original Equation 8; however, we now allow the model to not meet demand.

- Equation 39 can be used to limit the total number of shortfalls in power supply over all scenarios and all time steps.
- Equation 40 can be used to limit the number of shortfalls per each scenario *s*.
- Equation 41 can be used to limit the total number of shortfalls over all scenarios.

Our model can help the EMC to establish a day-ahead plan that defines how the fuel-based generators and the battery should be run to minimize the cost. In some electric grids, there are some tasks that require considerable amounts of electricity and that can be temporary delayed. For example, in some military establishments, the charging of electric vehicles and the use of pumps to fill water cisterns are tasks that can be temporarily delayed. The time to execute such tasks can be defined as a new decision variable that the model can control. To minimize the total operating cost, the solver will decide when it is more cost efficient to execute those tasks.

We analyzed in the thesis the uncertainty of the weather forecasts, but we considered a deterministic load. Based on the historic load data of the DLIFLC, we showed that the load had a consistent behavior. However, the load in some electric grids can differs considerably from one day to another. For that reason, we suggest that future research model the uncertainty of the load.

The configuration of the model in terms of the number and characteristics of fuel-based generators, energy storage units, wind turbines and PV panels was fixed during our analysis. However, our model could easily be modified so as to help design the optimal configuration. For example, one might allow the model to decide whether we really need to include energy storage, and if so, what is the appropriate storage capacity.

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